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CONTAGION RISK FOR AUSTRALIAN AUTHORIZED DEPOSIT TAKING INSTITUTIONS

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ABSTRACT

This paper investigates the contagion risk for Australian-owned authorized deposit taking institutions (ADIs) spilling from the US and UK banks. We hypothesized that Australian ADIs are prone to extreme shocks experienced by its US and UK counterparts. We define four discrete events for the Australian banking sector in terms of the number of banks exceeding at a time an extreme value. The extreme value is defined as the 90th percentile on the negative tail of the distribution of changes in the distance to default obtained through Black and Scholes (1973) and Merton (1974) formula. Then we fit a multinomial logistic model (MLM) to relate these events to the number of exceedances (extreme events) occurring in the US and the UK in the previous day for the time period September 2006 to September 2011. The MLM estimates reveal strong contagion effects for Australian ADIs from the US and UK banks.

JEL Classifications: G1, Q4

Keywords: *Authorized deposit taking institution (ADI), Contagion risk, Extreme value theory, Distance to default, Multinomial logistic model.*

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I INTRODUCTION

This paper examines contagion risk for Australian-owned authorized deposit-taking institutions (ADIs) and their likelihood of experiencing extreme shocks in the wake of such shocks in their US and UK counterparts. Borrowing from extreme value theory (EVT), we define an extreme shock as a large value down the negative tail of the distribution of changes in the distance to default (ΔDD). Distance to default (DD) is a popular measure of the financial strength of a firm, the difference between a firm's assets and liabilities at a given point in time: the larger the DD the financially healthier the firm, and the smaller the probability of default. We consider an extreme shock to have occurred if it exceeds the 90th percentile (the 10th smallest value) of its distribution. We define some discrete events in the Australian banking sector in terms of the number of ADIs experiencing extreme shocks, and label an event a crisis if three or more ADIs simultaneously exceed the extreme value. We fit all these events in a multinomial logistic model (MLM) to examine whether extreme shocks in Australia can be explained by extreme shocks in the US and UK.

Australia's banks have been healthier over the last decade than banks in other advanced economies like the US and UK. They performed remarkably well during the 2008 global financial crisis (GFC). Although they suffered funding pressure immediately afterwards, they recovered from that liquidity shortfall quickly. There was no bank failure, and only a small increase in nonperforming loans (NPL).

The strength of Australian authorized depository institutions (ADIs)[3] in terms of capital adequacy has grown steadily since 2007. Their capital adequacy ratio rose to 12.07 percent by the quarter ending March 2013, from 10.31 percent in December 2007. The strong trend in capital adequacy has been accompanied by a rising share of Tier 1 capital in total capital, reflecting both new capital raising and a shift toward lower-risk assets. Profitability also improved after a drop during the GFC, with annualized after-tax return on equity rising to 13.04 percent in December 2012 from 4.6 percent in September 2009 (APRA 2013).[4]

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[3] Australian authorized deposit taking institutions comprise mostly banks. According to the list provided by the Australian Prudential Regulation Authority (APRA), the number of ADIs in operation in September 2013 was 165 (excluding other ADIs). These were 22 Australian-owned banks, 8 foreign banks, 40 branches of foreign banks, 9 building societies and 86 credit unions.

[4] See IMF (2012) for a review of recent developments in the Australian financial sector.

[Insert Figure 1]

This apparent strength does not rule out threats and vulnerabilities in the future. A key worry for Australia is that its banking sector is dominated by four large banks, popularly known as the big four. By and large their business models are the same, and they are therefore exposed to similar threats. More specifically, they have similar degrees of dependence on offshore funding, which exposes them to common shocks and disruptions in international financial centres; they are not immune to contagion risks from banks operating in other countries.

It is useful to be able to determine the probability of financial distress for Australian banks arising from spill-over from international banks, particularly those in the US and UK. How might the soundness of Australian deposit-taking institutions be affected when banks in these countries encounter turbulence? Studies of contagion risk for Australian ADIs have critical importance in the context of the slow recovery of the US economy from recession, the unresolved debt crisis in Europe, and more importantly concerns about Australia's economic strength with the fading of the mining boom (IMF 2012). Understanding how foreign financial shocks are transmitted into the domestic banking system is relevant to the design and implementation of policies that can make contagion less likely. These include prudential polices that reduce dependence on short-term wholesale funding, structural banking reforms that aim to limit the cross-border activities of banks, and offering responses to shock through liquidity support or other means.

Although a number of studies have investigated contagion across Australia and its developed counterparts, most of these (e.g. McNeils 1993, Valadkhani *et al.* 2008 and Brooks & Henry 2000) primarily address spill-over effects across stock markets. There is a dearth of studies addressing the contagion risk for Australian-owned banks. Recently Pais and Stork (2011) investigated contagion among banks and property sectors within Australia; but this is not the same as cross-border contagion. We differ from previous studies in both methodology and coverage. While most Australian studies have used vector autoregression (VAR)-based methods to analyze contagion across markets, we use the extreme value theory (EVT) framework. An advantage of EVT approach over VAR approach is that EVT better captures the phenomenon that large shocks are transmitted across financial systems differently from small shocks, providing a new perspective on cross-border contagion risk to Australian ADIs.

Our results suggest a strong association between extreme shocks in selected systemically important US and UK banks and those in Australian ADIs. Statistically significant evidence indicates that the probability of a crisis for the Australian banking sector (when three or more ADIs experience extreme shocks simultaneously) can be explained by extreme shocks experienced by big banks in the USA and UK. The MLM results also suggest that the dynamics of interest rates and volatility in global financial markets have a significant influence on the health of Australian ADIs. The global economy is uncertain and Australia is not immune to shocks in global markets; the information presented here will assist the Australian surveillance authority in monitoring developments in global economies in general and in US and UK banks in particular, and to institute appropriate policy measures as needed. Our findings concur with observations of a recent IMF report suggesting that the uncertainty for the Australian banking sector is likely to stem mainly from the unresolved European debt crisis, anemic growth in the US economy and reducing demand for commodities (IMF 2012).

This paper is organized as follows: Section 2 briefly reviews the literature and describes the methodology. Section 3 presents and interprets results, while Section 4 concludes the paper.

II METHODOLOGY

A majority of the studies dealing with contagion across financial markets have addressed the spill-over of volatility across financial centres within a vector autoregression (VAR) framework, a system of generalized autoregressive conditional heteroskedasticity (GARCH)-type volatility equations that express the volatility of one market in terms of the volatility of some other market. Work by Engle *et al.* (1990), Eun and Shim (1989), Hamao *et al.* (1990), Lin *et al.* (1994) and Theodossiou and Lee (1993) document evidence of volatility spill-overs in different directions. For example, Eun and Shim (1989) observe uni-directional spill-over from the US to other markets. Theodossiou and Lee (1993) label the US market the ‘exporter’ of volatility. Brooks and Henry (2000), McNeils (1993) and Valadkhani *et al.* (2008) find uni-directional volatility transmission from the US and UK to the Australian stock market, while Hamao *et al.* (1990) and Lin *et al.* (1994) find bi-directional volatility across the US, UK and Japanese stock markets. A second group of studies documents channels of contagion across financial institutions. A number of channels have been documented, including, among others, depositors’ expectations (Diamond & Dybvig 1983), information asymmetry between banks and depositors about the true value of loans (Gorton 1985; Chari & Jaganathan 1988), and overlapping claims across banks (Allen & Gale 2000): a similarity in these studies is the idea that contagion of banks within or across countries spreads from the liability side of balance sheet. In contrast, Tian *et al.* (2013) argue that contagion arises from uncertainties of bank assets.

Since the late 1990s, an emerging trend in studies of contagion has been the use of the extreme value theory (EVT), which deals with tail events of a distribution[5]. EVT is useful in analysing the behaviour of simultaneous extreme realizations or coexceedances (exceeding a given threshold by a number of agents simultaneously) of a variable observed in different geographic locations. The EVT approach captures well the phenomenon that large extreme shocks are transmitted across financial systems differently from small shocks. Some recent empirical studies using EVT to investigate contagion across banks are those of Bae *et al.* (2003), Chan-Lu *et al.* (2012), Gropp and Moerman (2004) and Gropp *et al.* (2006). Gropp *et al.* (2006) use a multinomial logit model to the changes in the distance to default of European banks to determine cross-border contagion within the region. Using an identical framework, Chan-Lu *et al.* (2012) investigate the probability of simultaneous exceedances among large international banks. Pais and Strok (2011) employ EVT to study the intra-sector and inter-sector contagion risk of 13 sectors in Australia and observe that of them, property sector has the highest degree of dependence on the banking sector. We apply EVT to analyze contagion across the Australian and the US and UK banks. Our methodology has similarities with Gropp *et al.* (2006) in that we use the distance to default (DD) to build an indicator variable measuring different states of a banking system. It is similar to Chan-Lu *et al.* (2012) in that we assume that contagion risk is associated with extreme negative co-movements in bank soundness.

In our attempt to determine whether extreme negative shocks to Australian ADIs' stability are associated with similar shocks experienced by major banks in the US and the UK, we begin by observing whether a bank, either Australian or foreign, has experienced a shock on any day during the period from September 2006 to September 2011. We define a shock as any event when an exceedance occurs for that bank; it is said to have occurred when a bank exceeds a predefined extreme value, the negative 90th percentile of the change in the distance to default (ΔDD). We derive shocks from the time series of distance to default (DD) because this is a useful measure of financial soundness that has been used in other studies (see, for example, Chan-Lu *et al.* 2012; Gropp *et al.* 2006). Following these studies we define DD for a bank as the standardized difference between the market value of the bank's assets and an estimated default point: a given size of the bank's liabilities. Again, following the existing literature, we consider the sum of deposits, short-term funds and half the long-term liabilities as the default point: simply put, DD is the difference between a bank's assets

[5] See Hull (2012: 314–321) for an introduction.

and its default point. We standardize (divide) this difference by the volatility (standard deviation) of assets so that the DD of an individual bank can be compared with that of other banks and derive a series of daily DD and observe exceedances (extreme shocks) over the sample period. It should be pointed out that an exceedance does not mean a default. A default occurs when a bank's assets fall below its default point, whereas an exceedance refers to an event when the change in the distance to default (ΔDD) exceeds the negative 90th percentile point.

None of the banks in our sample experienced a default during the sample period, but they did experience volatile and sometimes extreme changes in DD, e.g. falling beyond the 90th percentile on the left tail of the distribution of ΔDD where we assume contagion risk to be associated with extreme negative co-movements in bank soundness. We consider that distress in the banking system of one country increases the likelihood of distress in the system of another country over and above what would be implied by the normal interdependence that prevails between the systems; accordingly, the next step in our analysis is to test the hypothesis that exceedances in Australian banks are a function of exceedances in US and UK banks.

To test the hypothesis, we first control for some common shocks then consider a model that takes the number of simultaneous exceedances (coexceedances) for Australian banks as the dependent variable, and the number of coexceedances among US and UK banks at a prior time as the explanatory variables.[6] It is expected that correlations between banking systems vary over varying states of the economy: the dynamics of DD in a normal condition may be significantly different from the dynamics of DD in a turbulent time. Thus, the coefficients measuring the impact of the explanatory variables on the response variable are likely to vary depending on prevailing financial conditions. To capture this phenomenon, we classify the response (dependent) variable into four categories: tranquil (none of the banks' ΔDD exceeds the extreme value; disturbing (at least one bank experiences an extreme shock –that is ΔDD exceeds the extreme value); alarming (two banks experience extreme shock simultaneously); and crisis (three or more banks experience extreme shock at one time). We fit these events into a multinomial logistic model (MLM), which predicts the probability of each of these discrete events for Australia in terms of the exceedances of the UK and US banks. This is done after controlling for the influence of some common explanatory variables such as developments in the real economy or volatility in domestic and global markets. As past shocks are most likely to lead to a current shock for a bank, we consider an autoregressive term (lag

[6] We take a lag of one week (five working days) for an overseas shock to transmit to Australia.

of the dependent variable) on the right-hand side of our model. The following paragraphs describe DD–the measure of financial strength, from which we generate the response variables for the MLM.

2.1 Distance to Default (DD)

Figure 2 illustrates the idea of distance to default. The vertical axis of the figure measures the value of assets and liabilities in a natural logarithm. Suppose at time $t = 0$ (today) the value (equities + liabilities) of a limited liability firm is lnA_0 and its liabilities (present value of the principal) are lnL. The firm defaults if lnA_0 falls below lnL. That works for today ($t = 0$), but to predict a default at some future date, T, we need two pieces of further information: the expected change in the value the firm and its dispersion over the period T-t.

[Insert Figure 2 here]

If the expected change in the firm's value for a day (the average of the possible asset values path in Figure 2) is μ and its daily dispersion is σ_A^2, the expected value of the firm for the period T-t can be given by $ln(A_t) + (\mu - \sigma_A^2 / 2)(\mathrm{T} - t)$. The standardized difference between the default point (lnL in Figure 2) and the expected value of assets is DD, which over the time period T-t at can be expressed as:

$$DD_t = -\frac{ln(L) - \left[ln(A_t) + (\mu - \frac{\sigma_A^2}{2})(T - t) \right]}{\sigma_A \sqrt{T - t}} \qquad (1).$$

We need to derive a series of DD of daily frequency using this formula; but firm values are not observed on a daily basis so we simulate asset values using Black and Scholes's (1974) option pricing formula. Under this, when a firm issues one unit of equity (E) and one unit of a zero-coupon bond with face value of L and maturing at a future time T, the following relationships can be established between the firm's equity (E) and asset (A) at maturity: as long as the asset value (A) is below the value of liability (L), the value of equity (E) is zero because all assets are claimed by the bond holder. On the other hand, if the asset value (A) is higher than the principal of the zero-coupon bond (L), equity holders receive the residual value and their pay-off increases linearly with the asset value. Thus, equity is equivalent to a long position on a call option with the strike price equal to the face value of debt. Payoff to the equity-holders can be given by:

$$E_T = \max(0, A_T - L) \tag{2}$$

The firm's equity (the call option) is in the money if the expected value of assets exceeds the expected value of liabilities (the strike price).

Black and Scholes (1973) use equation (3) to define equity. We can see that the equation is a stochastic version of the balance sheet equation. The first term on the right is the expected value of assets and the second is the expected present (discounted) value of liabilities at time *t*. The liabilities are discounted on a continuous basis by the risk-free rate *r* for the period *T*-*t*. *N(d)* in equation (3) is the value of the standard cumulative normal distribution function for *d*.

$$E_t = A_t N(d_1) - Le^{-r(T-t)} N(d_2) \tag{3}$$

where

$$d_1 = -\frac{\ln(L) - [\ln(A_t) + (r + \frac{\sigma_A^2}{2})(T-t)]}{\sigma_A \sqrt{T-t}}, \text{ and } d_2 = d_1 - \sigma_A \sqrt{T-t} \tag{4}$$

Our goal at this stage is to generate a series of asset values, and equation (3) takes us close to that goal. Now we build a system of equations as (5) and solve the system for A_t and σ_A by the iterative process proposed by Löffler and Posch (2011), which requires solving a system comprising (*T+1*) equations for (*T+1*) unknowns. We choose to calculate a series of A_t spanning 260 days, motivated by convenience as well as by the fact that most structural models are used to produce one-year default probabilities. Setting (*T*-*t*) to 1 for each day within the preceding twelve months simplifies to a system like (5) comprising 260 equations.

$$\begin{aligned} A_t &= [E_t - L_t e^{-r_t} N(d_2)] / \mathrm{N}(d_1) \\ A_{t-1} &= [E_{t-1} - L_{t-1} e^{-r_{t-1}} N(d_2)] / \mathrm{N}(d_1) .... \\ &.... \\ A_{t-260} &= [E_{t-260} - L_{t-260} e^{-r_{t-260}} N(d_2)] / \mathrm{N}(d_1) \end{aligned} \tag{5}$$

We solve the system in iterations. The first iteration is to use guesses for the asset values A_{t-a} where *a = 0, 1, …260* and to set the asset volatility (σ_A) equal to the standard deviation of the natural logarithm of returns computed from A_{t-a} multiplied by the square root of 260. We take the sum of the equity and the default threshold as the initial guess for a firm's asset. The estimated default threshold (*L*) of an authorized deposit-taking institution is the sum of deposits, short-term funds and half the long-term liabilities. Daily values of these balance sheet items are interpolated from two balance sheet dates. The source of these and other pieces of balance sheet information is Bankscope–Bureau Van Dijk; the source of equity prices (*E*) is Datastream. The sample period is 30 September 2005 to 30 September 2011.

For any further iteration, $k = 1 \ldots end$, asset values and their standard deviations obtained in the previous iteration are plugged into equation (4) in order to find d_1 and d_2. Then we substitute the values d_1 and d_2 in equation (5) to find new A_{t-a}, and compute the asset volatility again. We continue until the procedure converges. To check convergence, we examine the change in the asset values from one iteration to the next. If the sum of squared differences between consecutive asset values falls below some small value such as 10^{-10} we stop. Once the series of A_t is obtained, σ_A of the series is computed for a moving window of 260 days.

The final input of the DD equation—the drift rate μ—is estimated using the capital asset pricing model (CAPM). We obtain a time-varying beta from the 260 preceding observations of excess returns: for the ADI this is the first difference of the ADI's return on asset minus the risk-free rate; for the market it is the market return minus the risk-free return.[7] We use 90-day dealer accepted bills and S&P ASX-200 as proxies for the risk-free asset and the benchmark market respectively for Australia; 3-month treasury bill rate and S&P 500 for the US; and 3-month treasury bill rate and FTSE-Local for the UK. The source of data for these variables is Datastream. The sample period again is 30 September 2005 to 30 September 2011, but because beta is obtained from a moving window of the preceding 260 observations, the date when we get beta for the first time is 29 September 2006. Accordingly, the DD calculation starts from this date (29 September 2006).
After obtaining the series of DD, we compute ΔDD over five days for each ADI in our sample using Equation (6).

$$\Delta DD_{i,t} = \frac{DD_{i,t} - DD_{i,t-5}}{| DD_{i,t-5} |} \quad (6)$$

The choice of a five-day period is motivated by previous studies. Chan-Lau *et al.* (2012) argue that extreme events are more significant if they are prolonged: events that last for only a day are of little

[7]Thus, *excess return on an ADI's asset* $= (A_t / A_{t-1}) - (1 + r_{f\,t-1})$ and *excess return on the market* $= (M_t / M_{t-1}) - (1 + r_{f\,t-1})$ where *A* is asset value, *M* is the market capitalization and r_f is the risk-free rate.

concern; and the use of weekly changes reduces 'noise' in the data. Thus, we end up with 1301 observations of ΔDD for each ADI for the period 5 October 2006 to 30 September 2011.

The next step is to find the exceedances within the distribution of ΔDD_i and create the outcome variable for the multinomial logistic model. As previously mentioned, we define the 90th percentile point on the negative tail as the threshold, and an exceedance (or extreme event) to have occurred at time t for the i^{th} sample if $\Delta DD_{i,t}$ exceeds the threshold. Then we count the number of simultaneous exceedances (or coexceedances) across the sample for each t and define an index y_t based on the four discrete events, *tranquil*, *disturbing*, *alarming* and *crisis*. This takes us to the final stage of the analysis: identifying the underlying forces of these events. To do that, we fit these discrete events into a MLM, chosen because our dependent variable (the four states of financial condition just described) is a count variable. The most popular models that fit count variables are binary choice logit or probit models, but these are not applicable here because our dependent variable takes more than just the numbers 0 and 1; multinomial logistic and ordered logistic models are more suitable for our context. Of these two, the MLM serves better because it does not restrict the marginal effects of switching from one response to another. Had we used ordered logit, the marginal effect of changing from tranquil to disturbance would have appeared the same as that of moving from alarming to a crisis event.

2.2. Multinomial Logistic Model (MLM)

Many studies have used logistic regression to determine the probability of extreme shocks. Bae *et al*. (2003) use binomial logistic regression to predict the probability of coincidence of extreme return shocks across countries within and across regions. Groop *et al*. (2006) and Christiansen and Ranaldo (2009) employ an MLM framework to measure the probability of large changes in DD. The response variable in a binomial regression takes two outcomes, whereas in the MLM it takes more than two discrete choices. The MLM predicts the probability of different choices from a designated set of explanatory variables. In order for the model to be identified, the multinomial logistic considers one of the various choices as the base outcome and the probability of different outcomes is computed as the ratio of the probabilities of a given outcome to the base outcome. As we assume outcome 4 (tranquil) as the base outcome, the, probability that the response variable (y) at time t is equal to the i^{th} outcome is given by (7):

$$p_{i,t} = \Pr(y_t = i) = \begin{cases} \dfrac{1}{1+\sum_{m=1}^{3}\exp(x_t\beta_m)}, & if\ i = 4\ (base\ outcome) \\ \dfrac{\exp(x_t\ \beta_i)}{1+\sum_{m=1}^{3}\exp(x_t\beta_m)}, & if\ i < 4 \end{cases} \quad (7)$$

where x_t is the row vector of the observed values of the explanatory variables for y_t. β_m is the coefficient vector for the base outcome and β_i is that of the i^{th} outcome (i = *1,2 and 3*). The MLM estimates β by the maximum likelihood method.[8]

2.3. Explanatory Variables

The key explanatory variable in our model is the contagion risk for Australian ADIs. Following Bae *et al.* (2003), we define this as the risk of Australian ADIs experiencing extreme shocks as a result of such shocks experienced earlier by banks in the US and UK. We use the number of exceedances among US and UK banks as the measure of the contagion risk for Australian ADIs. We justify this by the fact that contagion may be channelled through either direct or indirect linkages with banks operating in different geographic locations. For example, external linkages could stem from direct and indirect equity exposures of local banks to overseas banks or, conversely, from shareholdings of local banks by foreign banks, direct exposures through loan books, deposit and funding sources from overseas or from foreign banks operating in a particular country, payments and settlement systems, and holdings of credit risk transfer instruments written on assets held by local or overseas institutions. Contagion may also occur without any explicit link when a negative shock in one bank is misinterpreted by investors as a signal of diminished soundness in other banks, either in the same country or in a different country (Chan-Lu *et al.* 2012).

Shocks from the US or UK may not transmit to Australia in real time. We need to allow a reasonable space of time for a shock encountered by US or UK banks to be felt by Australians. The explanatory variable measuring contagion in our model is the number of exceedances for US and UK banks the day before an exceedance experienced by an Australian ADI.[9]

[8] For further description see Greene 2012, pp. 763–766.

[9] Recall that an exceedance occurs when a ΔDD falls below the smallest 10th value of the distribution of ΔDD and that ΔDD represents change in distance to default (DD) over 5 working days. DDs are computed for each

An auto-regressive pattern is a common phenomenon in financial time series. Fama and French (1996) and Jegadeesh and Titman (1993) note that short-term returns tend to continue; stocks with high returns in the previous twelve months tend to have high returns in the future. Christiansen and Ranaldo (2009), similarly, find that the number of extreme negative returns today is positively related to the number of extreme negative return yesterday. We find a similar pattern in the extreme events (exceedances) of Australian ADIs, as the transition matrix (Table 1) reveals. For instance, during the period October 2006 to October 2011, we observe a total of 179 crisis events; six are followed by a tranquil, 21 by a disturbing, 31 by an alarming, and 121 by a crisis event. We therefore add to our model an auto-regressive term of order 1: that is, a one-day lag in the number of exceedances for Australian ADIs.

[Insert Table 1 here]

We add some domestic and global factors to the model to verify the strength of the relationship between different extreme events for Australian ADIs and contagion from US and UK banks. For example, we control the relationship for developments in real economy using change in the 10-year Australian government bond yield. A positive relationship exists between a change in government bond yield and the change in the health of the economy: when the economy is in a bad state, the interest rate is decreased; and when it is in a good state, the interest rate is increased. Naturally, banks are likely to experience fewer extreme shocks in a good state than in a bad state of the economy. Thus an inverse relationship holds between a change in government bond yield and the probability of extreme shock.

We also control our model for influences from some other local sources. These include the conditional volatilities of the S&P ASX-200 financial price index, the Australian commodity price

day over the sample period from the simulated values of assets and liabilities. While simulating the value of assets and liabilities on a given day for banks in different countries, we take into consideration the time differences. When the Sydney market opens at 9 a.m. on, say, Friday, it is Friday at 1 a.m. in London, so Sydney opens 8 hours after London has closed for Thursday. Likewise, when Sydney market opens at 9.00 a.m. for, say, Friday, it is 7 p.m. on Thursday in New York, so Sydney opens for Friday two hours after New York closes for Thursday. We consider ΔDD for Australia at time t is contemporaneous with ΔDD for US and UK banks at time t-1, so a one-day lag in the number of exceedances for the US and UK banks is actually a lag of two calendar days.

index, the exchange rate against the US dollar, and the Australian property price index.[10] The source of the first three variables is Datastream, and of the Australian property prices is the Bank for International Settlement (BIS) database.[11] Another explanatory variable in our model is the conditional volatility of the global financial services price index, capturing shocks from the global financial markets. For the conditional volatilities (h_t) of the indices, we consider GARCH (1,1) given by equation (8).

$$h_t^2 = w + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}^2 \tag{8}$$

This model forecasts the variance h_t^2 of date t return (x_t) of an index as a weighted average of a persistence term (the constant w), yesterday's variance h_{t-1}^2, and yesterday's squared error ε_{t-1}^2 of the constant only mean model: $x_t = c + \varepsilon_t$; where x_t is the annualized log return of the index and c is the constant.

2.4. The Sample

Because the distance to default is calculated from market value of equity, we consider only the ASX-listed ADIs. Furthermore, our aim is to investigate contagion risk only for Australian-owned ADIs. This limits our sample to ten ADIs: National Australia Bank (NAB), Commonwealth Bank of Australia (CBA), Australia New Zealand Bank (ANZ), Westpac Banking Corporation (WBC), Bendigo and Adelaide Bank (BEN), Bank of Queensland (BOQ), Macquarie Bank (MQG), Suncorp-Metway (SUN), Rock Building Society (ROC), and Wide Bay Australia (WBA). Since our aim is to examine contagion risk for authorized deposit-taking institutions—not necessarily for banks—we have banks and building societies in our sample. For sources of contagion, we consider five US banks— Bank of America, Citigroup, JP Morgan Chase, Morgan Stanley, and Goldman Sachs; and five UK banks— HSBC, Lloyds, Barclays, Standard Chartered and the Royal Bank of Scotland. These are among the most influential banks on the planet. According to the financial stability board (FSB)[12] they are all systemically important in that the failure of any one of them could trigger a

[10] All these are measured in Australian dollars.
[11] We use the index of property price per existing dwelling covering eight major cities. This data set is available quarterly. Daily data is simulated by interpolation; see BIS (2013).

[12] The FSB is an advisory board hosted by the Bank of International Settlement (BIS). It coordinates at international level the work of national financial authorities and international standard-setting bodies, and develops and promotes the implementation of effective regulatory, supervisory and other financial sector policies.

global crisis. They are homogeneous, and each set reasonably represents the banking sector of the country.

III RESULTS

Table 2 presents the results of three specifications of MLM. Our dependent variable is a count variable measuring the number of exceedances. Based on these numbers, we define four levels of event. For example, a crisis occurs if on a given day three or more banks exceed the negative 90^{th} percentile of the distribution of changes in the distance to default, whereas a tranquil state obtains when there is no exceedance at all. The multinomial logistic regression estimates the coefficients of the explanatory variables corresponding to each of the states or outcomes, and predicts their probability using these coefficients. For the sake of identification, one outcome is treated as the base, which in this case is tranquil (no exceedance). Coefficients of the explanatory variables for the base model are set to zero; the coefficients of the explanatory variables for the other models represent change relative to the base model.

[Insert Table 2 here]

The explanatory variables *lag number of exceedances: US* and *lag number of exceedances: UK* measure the contagion effects for Australian ADIs. We observe that these variables are statistically significant across the various specifications, suggesting strong contagion spilling into Australian ADIs from US and UK banks. The statistical significance is even stronger for crisis compared with disturbing events, suggesting that the probability of a large number of exceedances in Australia is associated with contagion risk from the United States. As expected, the auto-regressive term *–one day lag number of exceedances: Au* turns up with a positive coefficient and strong statistical significance. *Change in 10-year Australian government bond yield* appears with a negative coefficient, suggesting an inverse relationship between the health of the real economy and the probability of extreme events for Australian ADIs. We have also found the Australian ADIs to be exposed to volatility in the global financial market. The positive coefficient of the explanatory variable, the global financial services price index, suggests an increase in the number of extreme events experienced by the Australian ADIs is associated with an increase in *volatility of the global financial markets*. We consider some other variables (Model 3, Table 2) presuming that they may explain the probability of extreme shocks for Australian banks. These variables include the *GARCH (1,1) volatility of Australian commodity prices, property price index* (urban dwellings in eight major cities) and the *exchange rate of Australian dollar against the US dollar*. Even after controlling for these variables, the contagion effects remain almost unchanged.

[Insert Table 3 here]

Table 3 presents the marginal effects of the explanatory variables on the predicted probabilities of crisis, alarming and disturbing states. The marginal effect is the derivative (slope) of the prediction function, which in the context of MLM is the change in the probability of a given outcome for each unit change in the explanatory variable. The slope of a function can be greater than one, even if the values of the function are all between 0 and 1. The probability of a crisis event for Australian ADIs on any day increases on average by approximately 2% and 3% when the number of exceedances increased by 1 on the previous day in the US and UK respectively. The probability of an alarming state for Australia on a given day increases on average by approximately 3% and 4% if the number of exceedances increased by 1 in the US and UK respectively on the previous day. Hence, the MLM results reveal strong contagion risk for Australian ADIs stemming from US and UK banks. These results are robust across various specifications. Table 4 summarizes the estimated probabilities of the different states of financial distress for the Australian ADIs; Figure 3 depicts the dynamics of the response variable.

[Insert Table 4 here]

[Insert Figure 3 here]

In order to verify the strength of the contagion effects, we consider only the lag distance to default of individual ADIs in Model 5 and Model 6 (Table 5). Our dependent variable is derived from the distance to default, but DDs themselves can explain only 16% to 18% of the variation in the dependent variable as indicated by the McFadden's adjusted pseudo R^2, whereas the pseudo R^2 increases to 40% as the contagion effects are added (Model 4). Overall, the pseudo R^2 ranges from 37% to 40% over different specifications, suggesting that the data considered in the study fits the model well. The chi-squared and corresponding p-values indicate the joint significance of the explanatory variables. The results are robust over different time periods.

[Insert Table 5 here]

[Insert Figure 4 here]

Our sample spans 2006 to 2011, a period involving both tranquil and turbulent times for global markets. It is likely that the estimated probabilities are skewed to particular subsets of the sample. For example, the probability of crisis events is higher in 2008 (during the GFC) than in relatively calm years, as Figure 4 reveals. Given this, we use dummy variables to capture the effects of different years; their incorporation makes no change in the estimated coefficients or signs. In addition, we consider different time periods: for example, the sample period for models 1 and 2 is January 1, 2007 to September 30, 2011, and for model 3 is September 29, 2005 to September 30, 2011 (Table 2). Again, there is no observable difference in the output as far as sign, size and statistical significance of contagion effects are concerned.

Finally we check the robustness of our estimates against possible endogeneity and multicollinearity. The explanatory variable measuring extreme shocks for the US and UK banks in our model is likely to have endogeneity as a result of unobservable individual heterogeneity driving both the dependent variable (extreme events defined in terms of exceedances for Australian banks) and the explanatory variable itself. Two instrumental variable (IV) approaches have been widely used in empirical research to address endogeneity: two-stage predictor substitution (2SPS); and two-stage residual inclusion (2SRI).[13] Both methods entail estimating an equation in which the endogenous regressor is the dependent variable. In 2SPS, the predicted values from the first stage regression replace the endogenous regressor in the second stage. In 2SRI, the first-stage residuals, rather than the first-stage fitted values, are included in the second stage along with the observed values of the endogenous regressor.

Adopting a two-stage approach in our study means that we first estimate an extreme shock (exceedance) equation for both the US and UK:

$$z_i = bW_i + \varepsilon_i \tag{9}$$

where z_i is the extreme shock indicator for country i (US or UK), W_i is a matrix of explanatory variables that affect these indicators, b is the vector of unknown parameters to be estimated, and ε_i is the vector of error term. Using 2SPS, we estimate our outcome equation:

$$y_i = \alpha_{us}\hat{z}_{us} + \alpha_{uk}\hat{z}_{uk} + \beta X_i + u_i \tag{10}$$

[13] See for example Terza *et al* (2008) and citations therein. For description see Cameron and Trivedi (2009).

where y_i is the outcome vector (tranquil, disturbing, alarming or crisis), $\hat{z}_{us}$ and $\hat{z}_{uk}$ are the instruments for extreme shocks for the US and UK respectively—that is, the fitted values of z_i obtained from estimating Equation (9), X_i is the matrix of exogenous explanatory variables, β is the vector of unknown parameters to be estimated, and u_i is the error term. For 2SRI, we replace z_s with residuals obtained from (9), and estimate the outcome equation:

$$y_i = \alpha_{us}\hat{\varepsilon}_{ius} + \alpha_{uk}\hat{\varepsilon}_{iuk} + \beta_i X_i + u_i \qquad (11)$$

Recall that X_i in (11) includes both exogenous and endogenous regressors. We specify both (10) and (11) as multinomial equations and estimate them using the method of maximum likelihood. There is no specific direction as to the choice of specification for the first stage estimation. Angriest and Krueger (2001) use OLS for the first stage, arguing that consistency of the estimates from the second stage IV regression does not require that the first-stage functional form be correctly specified. Terza (2008) recommends a nonlinear specification in the first stage if the second-stage specification is nonlinear as well. We use both OLS and multinomial logit to obtain the first stage estimates (Table 6). Both methods reveal a statistically significant positive link between extreme shocks in US and UK banks and extreme events in Australian banks.

[Insert Table 6 here]

Now we consider multicollinearity. Two types of collinearity may exist among the regressors: perfect collinearity and near-collinearity. Perfect collinearity appears when one variable is perfectly correlated with other explanatory variables. None of the explanatory variables in our models is found to achieve this.[14] To check near collinearity among the regressors we estimate the variable inflation factor for the explanatory variables in Model 3 (see Table 2).[15] The rule of thumb is that there is evidence of near-collinearity if the largest VIF is greater than 10. We find two variables in Model 3, *volatility of Australian commodity price index* and *volatility of Australian property price index*, to have a VIF greater than 10; but as we can see in Table 2, inclusion of these variables makes no significant difference to the estimated coefficients of the variables measuring contagion risk for Australian banks.

[14] We estimate our models using STATA which drops such variable by default.

[15] See Baum (2006) for description.

IV. CONCLUSION

This paper studies the contagion risk for Australian-owned ADIs transmitted from the US and UK banks. We model extreme shocks for Australian ADIs as a function of extreme shocks experienced by the US and UK banks. Four discrete states of financial conditions were defined in terms of the number of banks exceeding at a time the predetermined extreme value. For example we defined crisis for Australian ADIs as a discrete event when three or more of them exceed the predetermined extreme value. Then we attempt to find the probability of that event in terms of contagion effect from the US and UK banks and a set of explanatory variables including the 10-year Australian government bond yield, conditional volatility of Australian financial sector price index, Australian commodity price index, exchange rate and Australian property index.

Our research finds evidence of strong association between these indicators and the explanatory variables; it suggests a statistically significant positive relationship between the probability of a crisis event and contagion effects from the US and UK banks. The MLM results also indicate that long-term Australian government bond yield and volatility in financial markets significantly explain the probability of the different states of financial health for Australian ADIs. As the global economy is uncertain and Australia is not immune to shocks in global markets, the Australian surveillance authority should closely monitor developments in global economies in general and those in US and UK banks in particular, and directs policy measures accordingly. For example an extra capital buffer for contagion risk should be put in place for the major Australian banks especially when the big US and UK banks experience financial turbulences.

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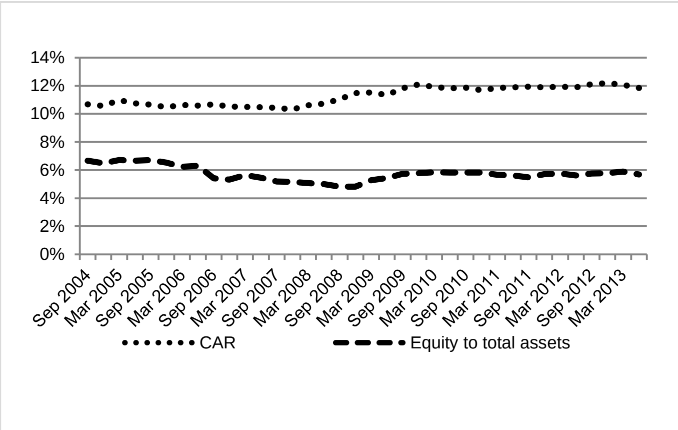
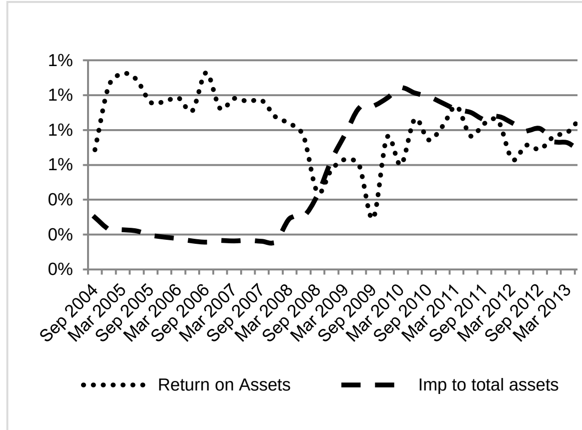
Figure 1: Performance Australian ADIs during September 2004 – March 2013

Panel A: Capital Adequacy Ratio and Shareholder Equity to Total Assets



Panel B: Return on Asset and



Notes: Impaired assets are those in arrear for 90 days. Source: APRA (2013)

Figure 2: Distance to Default

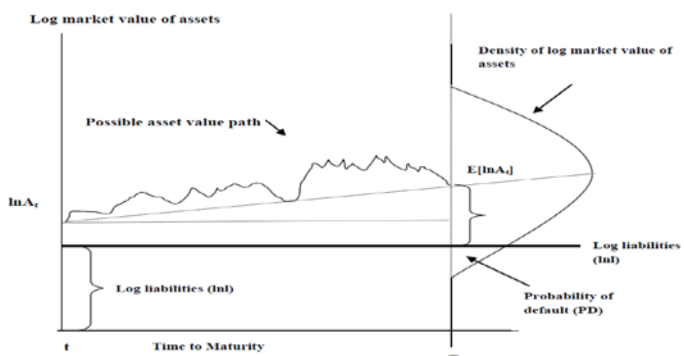


Figure 3: Probability of Different State of Financial Distress for Australian ADIs: Multinomial Logistic Estimates

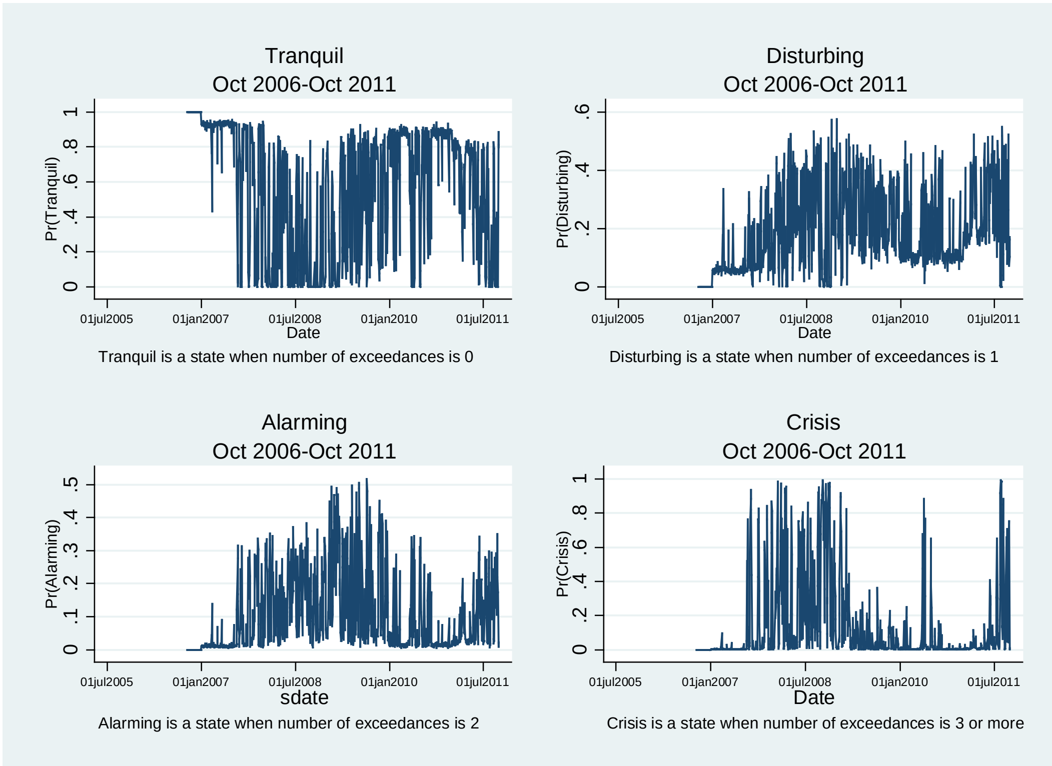


Figure 4: Probability of Crisis Event

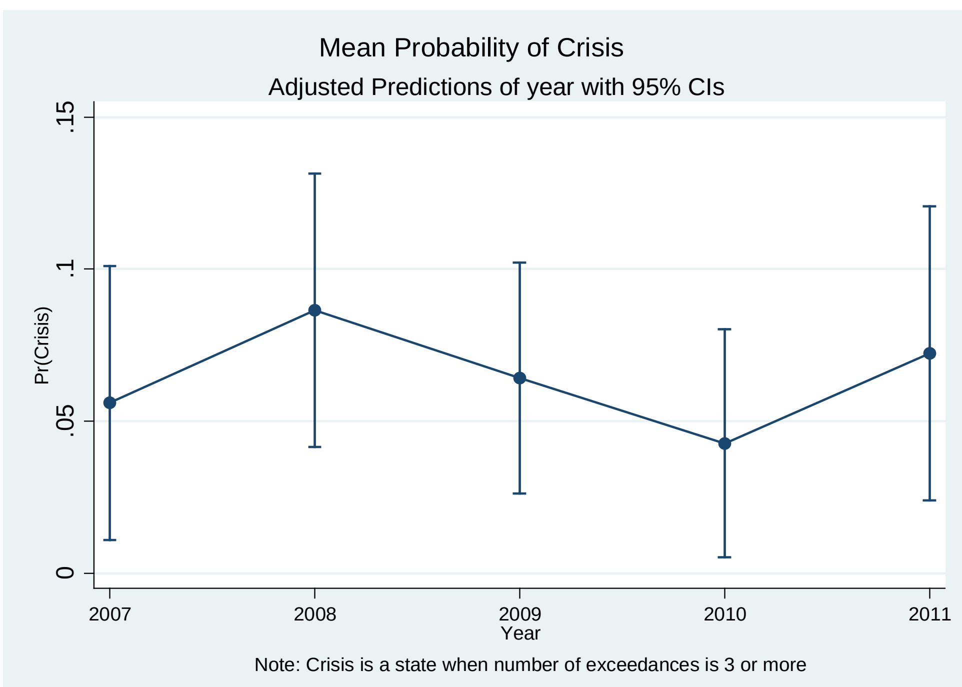


Table 1

Transition Matrix of the Extreme Events for the Australian ADIs

	Tranquil	Disturbing	Alarming	Crisis	Total
Tranquil	633	85	10	9	737
	(0.86)	(0.12)	(0.01)	(0.01)	(1.00)
Disturbing	78	108	47	19	252
	(0.31)	(0.43)	(0.19)	(0.08)	(1.00)
Alarming	20	38	44	30	132
	(0.15)	(0.29)	(0.33)	(0.23)	(1.00)
Crisis	6	21	31	121	179
	(0.03)	(0.12)	(0.17)	(0.68)	(1.00)

Figures represent the number of a row event followed by a column event. Thus, 633 is the number of times a tranquil event is followed by a tranquil event, 85 is the number of times when a tranquil event is followed by a disturbing event. Figures in parenthesis are the probabilities.

Table 2
Multinomial Logistic Estimates: Coefficients

Crisis	Model 1	Model 2	Model 3
Lag number of exceedances: AU+	2.5383***	2.5383***	2.4348***
Lag number of exceedances: UK++	0.7612***	0.7612***	0.7698***
Lag number of exceedances: US++	0.5668***	0.5668***	0.5814***
Change in 10-year Aus government bond yield	-7.0492**	-7.0492**	
Volatility of Australian financial price index	-22.5696	-22.5696	-29.7529
Volatility of World financial price index	62.3534*	62.3534*	51.4260†
Volatility of Australian commodity price index			312.360
Volatility of exchange rate (AU$/US$)			1.2816
Volatility of Australian property price index			-141.915†
Dummy: 2008	0.2701		0.4134
Dummy: 2009	-0.1437	-0.4139	-0.2919
Dummy: 2010	-0.9618	-1.2320*	-0.9355
Dummy: 2011		-0.2701	
Dummy: 2007	-0.9079	-1.1780*	-0.7924
Dummy :2006		-34.6115	
Constant	-5.5721***	-5.3020***	-7.1685***
Alarming			
Lag number of exceedances: AU	2.0571***	2.0571***	1.9670***
Lag number of exceedances: UK	0.5066**	0.5066**	0.4822**
Lag number of exceedances: US	0.4726**	0.4726**	0.5394***
10-year Aus government bond yield	-6.6043***	-6.6043***	
Volatility of Australian financial price index	-53.6977	-53.6977	-59.6569†
Volatility of Australian financial price index	49.4490*	49.4490*	46.2213†
Volatility of Australian commodity price index			381.7514
Volatility of exchange rate (AU$/US$)			-2.686
Volatility of Australian property price index			-205.1899
Dummy: 2008	0.3217		0.2588
Dummy: 2009	0.5129	0.1912	0.3438
Dummy: 2010	-0.7022	-1.0239*	-0.9149†
Dummy: 2011		-0.3217	
Dummy: 2007	-0.9753†	-1.2970**	-1.1175*
Dummy: 2006		-36.4316	
Constant	-3.4908***	-3.1691***	-5.0053***
Disturbing			
Lag number of exceedances: AU	1.4523***	1.4523***	1.3893***
Lag number of exceedances: UK	0.2607†	0.2607†	0.2518
Lag number of exceedances: US	0.4428***	0.4428***	0.4875***
10-year Aus government bond yield	-3.1699*	-3.1699*	
Volatility of Australian financial price index	-33.5374	-33.5374	-32.8516
Volatility of Australian financial price index	40.3820†	40.3820†	35.605
Volatility of Australian commodity price index			-171.1593
Volatility of exchange rate (AU$/US$)			-0.6674
Volatility of Australian property price index			215.1216
Dummy: 2008	0.04		0.0954
Dummy: 2009	-0.262	-0.302	-0.3339
Dummy: 2010	-0.6773*	-0.7173*	-0.6916*
Dummy: 2011		-0.04	
Dummy: 2007	-1.2880***	-1.3280***	-1.3021***
Dummy: 2006		-37.5367	
Constant	-1.6435***	-1.6035**	-1.9485*
McFadden's adjusted pseudo R^2	0.369	0.384	0.367
Log Likelihood	-734.7544	-734.7544	-736.9916
Chi^2	858.5695	914.7527	854.095
P (Chi^2)	0.00	0.00	0.00

Notes:

+Lag of one day.

++Lag of one day (or two calendar days after adjusting for the time difference among Australia, US and UK)

† p<0.1, * p<.05, ** p<.01, *** p< 0.001

Dependent variables are the different outcomes defined as follows. Tranquil: Number of exceedances = 0;; Disturbing: Number of exceedances = 1; Alarming: Number of exceedances = 2; Crisis: Number of exceedances ≥ 3. Base outcome is tranquil (no-exceedance). An exceedance occurs when a ΔDD falls in the negative 10% tail. Sample period is January 1, 2007 to September 30, 2011 for models 1 and 2 and September 29, 2005 to September 30, 2011 for model 3.

Table 3
Multinomial Logistic Estimates: Marginal Effects

	Model 1			Model 2		
	Crisis	Alarming	Disturbance	Crisis	Alarming	Disturbance
Lag number of exceedances: AU	0.0990***	0.168***	0.160***	0.0911***	0.168***	0.191***
	(6.87)	(9.02)	(6.54)	(6.36)	(8.9)	(7.46)
Lag number of exceedances: UK	0.0357***	0.0342†	0.0202	0.0329***	0.0361*	0.0288
	(4.19)	(1.91)	(0.73)	(4.14)	(2.12)	(1.02)
Lag number of exceedances: US	0.0195**	0.0409**	0.0565*	0.0171**	0.0382**	0.0637**
	(2.74)	(2.85)	(2.52)	(2.6)	(2.75)	(2.76)
10-year Aus government bond yield	-0.290*	-0.608**	-0.178	-0.269*	-0.600**	-0.272
	(2.48)	(2.64)	(0.57)	(2.56)	(2.76)	(0.86)
Volatility of Australian financial price index	0.905	-3.695	-0.173	0.679	-3.618	-0.0735
	(0.56)	(1.02)	(0.04)	(0.47)	(1.06)	(0.02)
Volatility of World financial price index	2.168†	4.098†	3.644	1.954†	3.932†	4.492
	(1.95)	(1.66)	(0.95)	(1.95)	(1.66)	(1.14)
Number of observations	992	992	992	1040	1040	1040

Notes:

[+]Lag of one day.

[++]Lag of one day (or two calendar days after adjusting for the time difference among Australia, US and UK)

† $p<0.1$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Figures in parenthesis are t statistics.

Dependent variables are the different outcomes defined as follows. Tranquil: Number of exceedance = 0; Disturbing: Number of exceedances = 1; Alarming: Number of exceedances = 2; Crisis: Number of exceedances ≥ 3. Base outcome is tranquil (no-exceedance). An exceedance occurs when a ΔDD falls in the negative 10% tail. Model 1 and Model 2 differs in the length of the sample period which is January 1, 2007 to September 30, 2011 for models 1 and September 29, 2005 to September 30, 2011 for model 2. The marginal effect of an independent variable is the derivative (slope) of the prediction function, which, in the context of MLM is the probability of a given outcome. The slope of a function can be greater than one, even if the values of the function are all between 0 and 1.

Table 4
Estimated Probability

States	Observation	Mean	Std. Dev.	Min	Max
Tranquil	992	0.546371	0.357018	0.000000	0.954297
Disturbance	992	0.200605	0.139455	0.000035	0.574599
Alarming	992	0.109879	0.117504	0.004571	0.516706
Crisis	992	0.143145	0.252746	0.000706	0.992943

Notes: Summary of the Probability of the outcome variable produced by multinomial logistic regression of Model 1.

Table 5
Multinomial Logistic Estimates: Coefficients

	Model 4	Model 5	Model 6
Crisis			
Lag number of exceedances: AU[+]	2.5246***		
Lag number of exceedances: UK[++]	0.4853		
Lag number of exceedances: US[++]	0.6415*		
Change in 10-year Aus government bond yield	-11.6302***		
Volatility of Australian financial price index	-91.9947		
Volatility of World financial price index	125.1649*		
Volatility of Australian commodity price index			
Volatility of exchange rate (AU$/US$)			
Volatility of Australian property price index			
Lag DD: WBC	-0.0210	-2.7688	-2.7721
Lag DD: NAB	1.6223	2.2082**	2.1270**
Lag DD: CBA	7.6554*	8.0183***	8.2489***
Lag DD: ANZ	-8.9590*	-8.6384***	-8.7656***
Lag DD: BOQ	3.0637	1.6123	1.6538
Lag DD: SUN	2.8280	-1.2215	-1.3019
Lag DD: BEN	-2.2598	-2.5817†	-2.6965*
Lag DD: MQG	-4.9272*	-6.0288***	-6.0105***
Lag DD: ROC	-0.3142	1.0408	0.9064
Lag DD: WBA	0.0654	5.8680**	6.0831**
Constant	-9.4525*	-5.7332***	-5.7163***
Alarming			
Lag number of exceedances: AU	2.0877***		
Lag number of exceedances: UK	0.4221		
Lag number of exceedances: US	0.4943*		
10-year Aus government bond yield	-10.2443**		
Volatility of Australian financial price index	-130.8641		
Volatility of Australian financial price index	57.8146		
Volatility of Australian commodity price index			
Volatility of exchange rate (AU$/US$)			
Volatility of Australian property price index			
Lag DD: WBC	0.5398	1.2621	1.2909
Lag DD: NAB	2.7836	1.8078*	1.7252*
Lag DD: CBA	1.175	7.1765***	7.4165***
Lag DD: ANZ	-4.6111	-7.9791***	-8.1171***
Lag DD: BOQ	6.1875†	2.3312	2.3645
Lag DD: SUN	-1.652	-2.6849*	-2.7798*
Lag DD: BEN	-3.374	-2.7526†	-2.8616†
Lag DD: MQG	-2.1633	-2.7423**	-2.7068**
Lag DD: ROC	-4.1449	-2.8637†	-3.0113*
Lag DD: WBA	2.6245	2.8614	3.0561†
Constant	-8.0587*	-4.4009***	-4.3784***
Disturbing			
Lag number of exceedances: AU	1.5043***		
Lag number of exceedances: UK	0.1778		
Lag number of exceedances: US	0.3686†		
10-year Aus government bond yield	-4.7283†		
Volatility of Australian financial price index	-6.383		
Volatility of Australian financial price index	37.89		
Volatility of Australian commodity price index			
Volatility of exchange rate (AU$/US$)			
Volatility of Australian property price index			
Lag DD: WBC	0.0651	-1.5877	-1.5712
Lag DD: NAB	-0.6468	0.7358	0.6289
Lag DD: CBA	1.3995	3.0191†	3.3074*
Lag DD: ANZ	-2.1572	-4.7177***	-4.8631***
Lag DD: BOQ	1.8393	2.2062	2.2346
Lag DD: SUN	-0.2509	-0.3109	-0.4446
Lag DD: BEN	-1.142	-1.5077	-1.6429
Lag DD: MQG	-0.9039	-1.3236†	-1.2678†
Lag DD: ROC	-2.1205	-1.7651	-1.9624†
Lag DD: WBA	3.165	3.2665*	3.5412**
Constant	-1.6496	-2.1878**	-2.1651**
McFadden's adjusted pseudo R^2	0.401	0.168	0.187
Log Likelihood	-350.9098	-727.7043	-728.7715

Notes:
[+]Lag of one day.
[++]Lag of one day (or two calendar days after adjusting for the time difference among Australia, US and UK)
† p<0.1, * p<.05, ** p<.01, *** p< 0.001
Dependent variables are different outcomes defined as follows. Tranquil = 0 exceedance; Disturbing: Number of exceedances = 1; Alarming: Number of exceedances = 2; Crisis: Number of exceedances ≥ 3. Base outcome is tranquil (no-exceedance). An exceedance occurs when a ΔDD falls in the negative 10% tail. Sample period is January 1, 2007 to September 30, 2011 for models 4 and 5 and September 29, 2005 to September 30, 2011 for model 6.

Table 6
Estimates from 2SPS and 2SRI

	2SPS	2SRI
Crisis		
Lag number of exceedances: AU	2.4348***	2.4942***
Predicted Values (xb_uk)	1.1329***	
Predicted Values (xb_us)	0.8035***	
Lag number of exceedances: UK		0.8839***
Lag number of exceedances: US		0.4683**
Residual: UK		0.9288***
Residual: US		0.1648
Alarming		
Lag number of exceedances: AU	1.9670***	2.0158***
Predicted Values (xb_uk)	0.7096**	
Predicted Values (xb_us)	0.7455***	
Lag number of exceedances: UK		0.5569**
Lag number of exceedances: US		0.4567**
Residual: UK		0.7438***
Residual: US		0.1749
Disturbing		
Lag number of exceedances: AU	1.3893***	1.4419***
Predicted Values (xb_uk)	0.3706	
Predicted Values (xb_us)	0.6738***	
Lag number of exceedances: UK		0.2726†
Lag number of exceedances: US		0.4460**
Residual: UK		0.5259**
Residual: US		0.2745
McFadden's adjusted pseudo R^2	0.367	0.377
Log Likelihood	-736.9916	-724.6674

Notes:
This is an excerpt of the actual estimates presenting only the variable of interest namely the indicator of extreme shock (exceedances). The table with full coverage could be provided if required.
+Lag of one day.
++Lag of one day (or two calendar days after adjusting for the time difference among Australia, US and UK).
† p<0.1, * p<.05, ** p<.01, *** p< 0.001
Dependent variables are different outcomes defined as follows. Tranquil = 0 exceedance; Disturbing: Number of exceedances = 1; Alarming: Number of exceedances = 2; Crisis: Number of exceedances ≥ 3. Base outcome is tranquil (no-exceedance). An exceedance occurs when a ΔDD falls in the negative 10% tail. Sample period is January 1, 2007 to September 30, 2011. Fitted values (xb_uk and xb_us) and residuals for the outcomes are obtained via multinomial logit.