# Contagion Risk in the Australian Banking and Property Sectors

by Amelia Pais and Philip A. Stork[1]

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**Abstract**

The Australian banking system has emerged from the global crisis as one of the strongest in the world with consistent high profits, healthy capital ratios and AA credit ratings. Are there any risks or vulnerabilities in this success story? This paper looks at systemic banking risk or contagion risk in Australia and attempts to determine if this risk has increased with the recent global crisis as well as whether the risk is related to the downturn experienced in the real estate market. We employ Extreme Value Theory to measure univariate Value at Risk and Expected Shortfall, as well as multivariate intra-sector and inter-sector contagion risks. Of the 13 sectors analyzed, we find that the property sector exhibits the highest level of extremal dependence with the banking sector. Further, the credit crisis has significantly increased the probability of a bank or property firm crashing. Moreover, contagion risks have increased significantly not only within the banking and property sectors, but also between them.

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[1] Pais and Stork are at Massey University. Thanks are due to Paul Kofman and to seminar participants at Auckland University of Technology and Massey University. Address correspondence to P. Stork, Massey University, College of Business, Department of Economics and Finance, QB 3.39, Private Bag 102 904, North Shore Mail Centre, Auckland, New Zealand. E-mail: p.a.stork@massey.ac.nz. Phone: 00 64 9 414 0800, extn. 9226.

## 1. Introduction

Since mid-2007 the world economy has experienced a severe financial crisis. It originated in the US subprime mortgage market and then spread to the rest of the world; in its wake this crisis has caused the failure of banks in many countries including the US, UK, Spain, Germany, Iceland, Ireland and Hungary among others (Reinhart and Rogoff, 2009). The crisis has also affected activity in the real economy; the World Bank forecasts the global real GDP to contract by nearly 3 percent during 2009 ("Prospects of the World Economy," World Bank webpage). Two channels have contributed most to the spread of the crisis globally: the first is the direct exposure of financial institutions around the world to the US subprime mortgage market through securitization and credit derivatives[2]; the second is through common shocks to asset markets, especially the real estate markets.

Regulators and analysts blame financial institutions' excessive risk taking for their subsequent problems. For banks, the shift to higher risk was driven by low interest rates, aggressive lending growth and the use of securitization to increase their risk rather than diversify. In this move the banks expanded their balance sheets and maximized the opportunities for capital arbitrage. Real estate lending, specifically housing lending, has been at the center of the crisis. Many countries around the world have experienced "real estate bubbles" since the beginning of the 2000s (see Reinhart and Rogoff (2009)). The collapse of the housing markets has sparked concern about the unsustainable levels of debt in many economies and about banks' capital adequacy. A marked increase in risk aversion and the breakdown of credit markets around the world, especially the interbank market, have also played a part in the unfolding of the crisis and the decreases in banks' share prices.

The previous recounting of events is not an exclusive feature of the current crisis: Reinhart and Rogoff (2008a, 2008b, 2009) find that financial crises are led by long and sustained asset market collapses and are followed thereafter by drops in GDP, increases in unemployment and increases in government debt associated with the costs of bailing out the banking systems and implementing stimulus packages to bolster the economy. More specifically, credit losses subsequent to the collapse of asset markets have been consistently identified as one of the main

[2] Ostrup et al (2009) cite a source which estimates that one third of US mortgage-backed securities have moved offshore, particularly to Europe.

triggers of bank failures, particularly as losses from non-performing loans reduce the value of banks' equity and compromise their solvency. Laeven and Valencia (2008) claim that general increases in credit losses are usually accompanied by large drops in real estate and equity prices. During the Japanese banking crisis of 1997, for example, banks suffered from large drops in the value of real estate and the equity used for loan collaterals; at the peak of the crisis non-performing loans accounted for 35 percent of all loans in the system. Further, the Norwegian banking crisis of 1991 occurred after a sizeable correction in property prices and high interest rates increased the volume of banks' non-performing loans; in the years before the crisis the banks had lent heavily to residential and non-residential real estate, thus accelerating the run up of property prices (Laeven and Valencia, 2008). Moreover, Ostrup et al. (2009) argue that the mid-1980s Nordic countries' crises were triggered by drops in real estate values. Collier et al. (2003) have developed a test which shows that the US financial institutions which are more exposed to real estate lending (particularly construction and development loans) are more at risk of failure in the case of a real estate crisis.

The focus of this paper is the Australian banks because, in contrast to other countries, they have performed relatively well during the current financial crisis: Australian banks have not suffered significant losses related to real estate and housing lending and their share price index has fallen much less than the drops that occurred in the US, UK and other European countries. Moreover, all four so-called Australian "pillar" banks[3] have proven very resilient to the crisis; they are ranked among the top 20 safest banks for 2009[4].

The four-pillar policy is a specific feature of the Australian financial system designed to maintain the separation between the four largest banks (initially it also included the two largest insurance companies). It was first proposed in 1990 when the Government prevented a merger between ANZ and National Mutual, and was then extended to stop the four big banks from taking over or merging with one another. The objective of the policy is to ensure that the banking market remains competitive.

The apparent strength of the Australian banks suggests that they are relatively immune to shocks in the real estate sector and that contagion risk is less relevant for them. This could be the

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[3] ANZ, CBA, NAB and Westpac.

[4] On the "Global Finance" list, which annually selects the 50 safest banks through a comparison of the long-term Moody's, Standard & Poor's and Fitch credit ratings of the 500 largest banks around the world, see http://www.gfmag.com/tools/bank-rankings/2341-words-50-safest-banks-2009.htm.

result of the good preventive work done by the Australian Prudential Authority (APRA). They have taken a proactive approach to supervision by, for example, coercing banks to run stress-tests on their housing portfolios in 2003 and 2004 and by increasing the capital requirements for low documentation loans in 2004 (RBA, 2009). APRA also applies a comprehensive version of Pillar II of Basel II, requiring supervised banks to have adequate capital to support all the risks inherent to their activities rather than only the risks addressed under Pillar I. Two of the risks specifically mentioned by APRA are contagion and reputation risks, especially when banks operate within larger business groups. APRA is also concerned with banks' ability to raise capital when needed, mainly economic capital which is made up by shareholder equity[5].

According to the "Financial Stability Review" published by the RBA in March 2009, Australian banks remain profitable but are facing the most challenging conditions they have had in years, with declining profitability and increasing problem loans. In particular, this paper looks at the systemic banking risk or contagion risk in Australia and attempts to determine if this risk has increased with the recent global crisis and to what extent this risk is related to large shocks in the real estate sector. Contagion risk is one of the most important problems of any financial crisis for three reasons: 1) it requires intervention; 2) it can lead to a meltdown in the financial system; and 3) it poses substantial costs to the economy as a whole (Allen et al., 2009). We also refer to Cole et al. (2009) who demonstrate the strong links between banks' financial soundness and future economic growth.

This paper uses Extreme Value Theory (EVT) to calculate three types of risk and the effect of the current financial crisis on those risks: first, *univariate risk*, which is the probability of large negative returns in a given stock; second, the *intra-sector contagion risk,* which is the probability that a strong decline in either a bank or property stock coincides with a simultaneous fall in another bank or property stock; and third, the *inter-sector contagion risk*, which looks at the extremal linkages between the Australian banking and property sectors by estimating the probability that a bank's stock price declines dramatically if there is an extreme negative shock to a property firm.

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[5] APRA uses two tools: Probability and Impact Ratings System (PAIRS) which assesses likelihood of failure and its impact on financial system, and the Supervisory Oversight and Response System (SOARS) which organises the response to prudential issues. Refer to APRA webpage, www.apra.gov.au; for information on the supervisory and prudential regime in Australia.

Banks' stock prices have been used regularly to assess banks' systemic risk because they have two advantages over balance-sheet measures or interbank exposures. First, they are readily available at the individual level; second, stock prices reflect the market's future valuation of the banks and therefore they should reflect the interdependencies among the banks in the system (Bae et al., 2003).

We also argue that as banks are commonly exposed to the property sector their stock prices should also reflect risks in that sector. Shocks to asset markets are of particular relevance to banks because they usually increase banks' credit risk. For example, Hess et al. (2008) found that credit losses in Australia are negatively related to the returns in both equity and housing markets. Lu and So (2005) examine the return relationships between listed banks and real estate firms for a group of Asian economies at the heart of the Asian crisis. They develop a three-index model and find returns on listed property firms Granger cause returns on banks (but not the opposite). They report that real estate lending was the main line of business in the Asian banks during the 1997-1999 Asian crisis, finding that the risks of real estate collateral on the banks' balance sheets became explicit and were recognized in the bank returns only after the crisis materialized.

We extend our analysis to include the New Zealand exposure of Australian banks because the New Zealand economy is of great importance to the Australian banks. Overseas exposures account for around 30 percent of Australian banks' total assets. New Zealand accounts for the largest share at around 40 percent, and the profits from the New Zealand operations represent between 10 and 20 percent of the total Australian bank profits. APRA specifically requires banks to ensure that they have enough capital to cover contagion risk arising for other institutions within their business group; the four largest New Zealand banks, which represent almost 90 percent of the New Zealand market, are subsidiaries of the four Australian pillar banks. The Australian and New Zealand banking systems are therefore highly interconnected.

Australia and New Zealand have both enjoyed a boom in real estate prices in recent years; see e.g. Girouard et al. (2006). In both countries, investors and banks alike have a preference for real estate assets; this preference has led to an overinvestment in that sector. The value of housing assets represents 60 percent of the total Australian household wealth (RBA, 2008) and in New Zealand it has recently reached 75 percent (Herring, 2006). Banks are in a very similar position: during 2005, the exposure of individual banks to the housing sector in NZ varied from 45 percent to almost 95 percent of total lending (Herring, 2006).

In Australia, the equity value of the property firms has fallen dramatically, and several construction companies have recently gone into bankruptcy (RBNZ, 2008). Australian listed property firms own around one-third of the domestic commercial property and have come under great pressure. In recent years they have significantly increased their leverage ratio to around 70 percent, half of which is financed by banks. Moreover, some foreign banks have already reduced their exposure to the Australian commercial property sector because of the sharp increase in non-performing loans over the last few years; the Australian Government is searching for ways to help the sector and to prevent problems from spreading to local banks (RBNZ, 2009). The decline in house prices of around 4 % since their peak in March 2008 and declines in share values during 2008 imply that for the first time in ten years household net worth has fallen by an estimated 10%, which is the largest decline in household net worth in several decades (RBA 2009). The banks are feeling the effects of crisis on their balance-sheet: the value of non-performing assets has increased from 0.4% to over 1% in a year. This increase in mainly driven by bad business loans, specially commercial property loans; the impaired assets ratio in banks commercial property portfolio is now at the highest level of the last 10 years: 3.3% in December 2008, compared to 1.5% a year earlier (RBA, 2009). New Zealand's banks reported a three-fold increase in impaired assets between March 2008 and December 2008 and indicated that there has been a further increase in impaired assets in the first half of 2009 (RBNZ 2009).

These increased risks had already been recognized by the IMF which in 2006 identified four issues of concern within the Australian financial system: the heavy exposure to housing and large household indebtedness; the high reliance on wholesale funding; the international exposure (mainly to New Zealand); and the contagion risk arising from both NZ and domestically because of high concentration in the market (IMF, 2006).

This paper makes two main contributions to the literature: first, it estimates contagion risk in Australia for the first time and includes the effects of the global financial crisis on banks' individual risk and systemic risk; and second, it measures the inter-sector risk contagion risk arising from the banks' exposure to real estate markets.

The paper is organized as follows: the next section reviews the literature on financial contagion; section 3 explains the econometric model; section 4 describes the data; section 5 presents the univariate results which are the probabilities of large negative returns in individual stocks; section 6 presents the multivariate results or contagion risk; section 7 further analyzes the dependency between the property and banking sectors; and section 8 concludes.

## 2. Financial Contagion

Financial contagion among banks happens when problems in one bank spread to other banks in the system, see for example Karolyi and Stulz (1996) for a study into such a "domino effect." The vulnerability of banks to contagion creates systemic risk when problems in one financial institution or market spread across the financial system leading to bank runs by wholesale and retail depositors, and ultimately to failure. The literature on financial contagion focuses on two aspects: first, how to measure contagion; and second, how to determine the channels through which contagion takes place.

### *2.1 Measures of Financial Contagion*

There are different ways to measure financial contagion. Most are based on the idea that contagion is associated with extreme events, and evidence of contagion is seen when markets or asset prices move together after a shock in a way that cannot be explained by the fundamentals. The older literature uses correlation or covariance to measure contagion in times of crisis. For example, Shiller (1989) examined co-movements between US and UK stock markets which cannot be explained by differences in dividends. As Bae et al. (2003) point out, one problem with these approaches is that the large correlation of negative returns seen through contagion would be hidden or averaged out by the small or zero-correlation of normal returns. This is because financial contagion is associated with excess volatility and irrational panics so one would expect large negative returns to be far more correlated than small negative returns. Correlation is the measure of dependence in the center of the distribution and which gives little weight to extreme returns. As a result, the correlation measure may seriously over- or underestimate the risks from joint extreme events. Moreover, it is difficult to find evidence of contagion after a shock in markets which are highly correlated in periods of stability. It assumes the dependence to be linear and it assumes a Gaussian distribution. Longin and Solnik (2001) discuss the spurious relation between correlation and volatility. Forbes and Rigobon (2002) argue that another flaw of tests based on cross market correlations is that the estimations of the correlation coefficients are biased upwards if market returns are heteroskedastic. Market volatility usually increases in crisis periods; thus, unless the correlation coefficients have been corrected, the tests will appear to find contagion. We refer to Poon et al. (2004, p. 583) and to Straetmans et al. (2008, p. 3) for lucid discussions on the shortcomings of the correlation measure.

Another approach is based on estimating conditional probabilities of extreme returns in certain stocks or markets given large returns in other stocks or markets: Bae et al. (2003) use multinomial logistic regression to estimate probabilities of extreme returns in Latin American countries given extreme returns in Asian economies. Exceedances are defined as returns below the 5$^{th}$ percentile and co-exceedances as joint occurrences of such extreme returns in a given day and for a given region. They use Monte Carlo simulations to make sure that the apparent contagion is not simply the outcome of a study on large returns. Chan-Lau et al. (2007) use a binomial logit regression to determine the likelihood that a large shock to one bank would cause stress to a counterpart bank.

A recent group of papers, for example Hartmann et al. (2004, 2006) and Straetmans et al. (2008) use extreme value theory (EVT) to measure contagion. Because this method is non-parametric, there is no need to assume a normal distribution of returns or constant variance-covariance matrices. EVT is well suited to examine contagion because it focuses on extremely rare events such as bank failures or market crashes. The first step is to calculate so-called conditional-co-crash (CCC) probabilities; this is done both to measure extreme spillover risk and to assess crash probabilities conditional on aggregate or systematic shocks that affect the whole market. EVT also provides a straightforward means of estimating extreme quantiles, including Value at Risk numbers but without the problems associated with fitting a parametric distribution to a set of observed returns or using historical simulation.

### *2.2 Channels for Contagion among Banks*

There are two potential channels for contagion among banks (Gropp and Hartmann, 2004):

The first is through exposure in the interbank and Euromarkets. Banks use both markets to manage their levels of risk and especially liquidity risk which banks tend to manage at the margin: the failure of one bank can therefore have a very damaging effect on the liquidity positions of other banks which may result in their collapse. For example, Allen and Gale (2000) develop a theoretical model in which the channel of contagion consists of the overlapping claims that various sectors or banking systems have on one another. Several papers also look at this issue from an empirical point of view, for example Furfine (2003) who uses US federal funds data to measure the risk of contagion in the interbank market. He finds that although the bilateral credit exposures are not very large, the illiquidity risk created if one of the big banks is unable to borrow has the potential for great risk of contagion.

Duggar and Mitra (2007) examine whether or not the increase in internationalization of Irish banks has led to a higher risk of contagion. They measure the probability that Irish banks will have a large negative shock at the same time as banks in other countries. One of the possible links for contagion is the increased reliance in wholesale funding through the interbank market in recent years. The risk to banks is measured by the "distance to default." Shocks are measured by the weekly percentage change in the distance to default for each bank. Interdependences across banks are measured by simple correlations and one-year rolling correlations. They also use a logit model to estimate the probability of Irish banks having the largest negative shocks at the same time as banks in other countries. They find evidence of contagion from the US and the UK. Upper and Worms (2004) find that contagion risk in the German interbank market mostly affects the relatively small banks. However, in the absence of safety mechanisms such as deposit guarantees, the failure of one single bank can potentially bring down up to 15 percent of the German banking system.

The second channel is revelation of information. The source of contagion may be asymmetric information which arises when economic agents are unable to distinguish between good and bad banks. In this case a shock in a bank serves to predict shocks in other banks. There are several reasons why information asymmetry is more prevalent in the banking sector than in other sectors. Banks intermediate in information. They are opaque institutions which specialize in financing illiquid and non-marketable assets, with information frictions, and they sustain long customer relationships (repeated lending or repeated deposits contracts) in which the level of monitoring by the bank is important because it affects the asset return. At the same time the quality of the loans in a bank's portfolio is not observable by outsiders and there is large scope for changes in the composition of the portfolio (Flannery, 1994).

The contagion effect may also be indicative of investors correctly re-pricing the equity of banks in the presence of "new" rather than "incomplete" information. Banks offer relatively homogenous products to their customers and, as a result, they are collectively exposed to the same risks (Heffernan, 2005). In this sense the positive correlation of the return of loan portfolios of different banks will cause the contagion to happen without the need to assume incomplete information on the part of investors; i.e. the market correctly re-prices all the banks in the system which are exposed to the same type of risks.

De Vries (2005) proves that if banks' balance sheets can be seen as a linear combination of the underlying risks (on the asset and liability sides) and if financial returns have fat tails, then the potential for systemic risk is large. Banks are linked because their assets are exposed to the same risks andtherefore they share the same common macroeconomic drivers. Moreover, they are linked because banks frequently participate on the same loans through the syndicated loan market. On the liability side, banks are exposed to liquidity risk because competition and disintermediation of deposits implies that changes in interest rates affect the ability of banks to raise deposit finance and hence their liquidity. The fragility of the system or its vulnerability to contagion revolves around the fact that banks are exposed to the same risks. If the exposures to those risks have normal distributions then the potential for systemic risk is weak, but if the exposures behave in a non-normal way then the potential is strong.

Bessler and Nohel (2000) provide evidence that contagion effects after dividend cuts by US money-center banks were not driven by panic but rather were systematically related to risks common to announcing and non-announcing banks, and in particular by exposures to weak real estate markets, LDC's loans and highly-leveraged transactions. Moshirian and Wu (2009) find that banking industry volatility is a good predictor of systemic banking crises in developed markets. Their study is one of very few to use bank stock prices as a measure of concurrent market information of banks' wellbeing. Hartmann et al. (2006) use EVT to estimate two measures of fragility on the EU and US banking sectors. They argue that rational investors use all the information available regarding individual banks' risks and the linkages between banks to correctly price banks' equity; therefore, if a bank experiences a large shock to its equity price there will be a contagion effect if one or more banks in the system suffer extreme equity comovements. Systemic risk happens when the co-crash probability is conditioned on a general stock index co-movement.

### 3. Application of Extreme Value Theory

When assessing the likelihood of financial distress, we are only concerned about extreme negative returns. The more common returns, which are centered around the mean, are of less relevance. An ordinary Value-at-Risk (VaR) approach, based on the assumption of a normal distribution, is not appropriate for representing the most extreme risks as it fails to capture the tail behavior and in general underestimates the risk of large negative returns. EVT helps to fill up this gap as it focuses on the tail of the distribution function and provides a purely non-parametric method for the measurement of extremal dependence, which may be estimated by a single function that exists under fairly general conditions. EVT is particularly suited to assess extremely rare events for which, per definition, historical data samples are limited. This is because under certain rather weak assumptions the tails of the probability distribution functions display specific characteristics and can take only certain shapes. These functional regularities allow for estimation of the shape of the entire tail even if only very few extreme observations are available. Mandelbrot (1963) has already proposed that the tails of the distribution of commodity prices diminish by a power instead of an exponent, which is assumed under the (log)normal distribution. For various empirically relevant distributions, including the often representative Student-t, the probability of variable V exceeding tail value Q may be calculated as:

$$p = P\{V > Q\} = CQ^{-\gamma} \tag{1}$$

In equation (1) the parameter Q must be a value in the tail of the distribution and parameter C is a positive constant. As is common practice in the literature, we multiply the stock returns by -1 in order to work with upper tail returns. The parameter $\gamma$ represents the thickness of the tail of the distribution function and is commonly referred to as the tail index. If $\gamma$ is high, the tail is thin, whereas for low values of $\gamma$ the tail is fat. We use the Hill (1975) estimator to estimate the tail index $\hat{\gamma}$. We define $x_i$ as the i-th order statistic, thus $x_i \geq x_{i-1}$ for i = 2, .., T, in which T equals the number of observations. The tail index $\hat{\gamma}$ equals the inverse of the Hill estimator $\hat{\alpha}$, where:

$$\hat{\alpha} = \frac{k}{\sum_{j=1}^{k} \ln\left(\frac{x_j}{x_{k+1}}\right)} \tag{2}$$

In equation (2) the parameter k equals the number of higher order statistics used in the tail of the distribution. Following Hartmann et al. (2004, p. 317), a T-statistic is derived:

$$T = \frac{\hat{\gamma}_1(k_1) - \hat{\gamma}_2(k_2)}{\sigma\left[\hat{\gamma}_1(k_1) - \hat{\gamma}_2(k_2)\right]} \sim \mathrm{N}(0,1) \tag{3}$$

Where $k_i$ denotes the number of order statistics of stock i that are used to calculate tail index $\hat{\gamma}_i(k_i)$. The denominator's standard deviation is calculated as the bootstrapped difference $\hat{\gamma}_1 - \hat{\gamma}_2$. We opt for bootstrapping in blocks because of the nonlinear dependencies that might be present in the return data. Following Hartmann et al. (2004), we set the number of block bootstraps equal to 600. The optimal block length is fixed at $T^{1/3}$, following Hall et al. (1995). The T-statistic may for instance be used to test for equality of the left and right tail index estimates (asymmetry test) or for structural temporal changes.

Although the α-estimate reflects the shape of the tail of the distribution, we need other yardsticks to measure the risk of a large fall in a share price. To that purpose we calculate the VaR and Expected Shortfall (ES) as follows:

$$VaR = x_{k+1}\left(\frac{k}{Tp}\right)^{1/\hat{\alpha}} \tag{4}$$

And

$$ES = \frac{\alpha}{(\alpha - 1)} VaR \tag{5}$$

In equation (4) the VaR equals the maximum one-day fall in the share price one may expect in the p percent worst day. In equation (5) the ES measures the expected *size* of the p percent worst day, an aspect on which the VaR contains no information. As we focus on the extreme events, i.e. when serious financial distress occurs, we set the probability p at a high level of, for instance, 99.9 percent. We refer to Novak and Beirlant (2006) for a recent example of an EVT-based estimate of the ES of a stock market index.

In addition to the above univariate risk assessment, we are also interested in the extremal linkage between Australian and New Zealand property firms and banks. We estimate multivariate extreme spillover risk, which determines how likely it is that the stock price of a bank or property firm crashes jointly with that of another bank or property firm. We build on the work of Hartmann et al. (2004) and Straetmans et al. (2008). For all stocks i = 1,..,N, the crash levels or extreme quantiles $Q_i$ are set at equal values, thus:

$$P\{V_{1t} > Q_1\} = .. = P\{V_{it} > Q_i\} = .. = P\{V_{Nt} > Q_N\} = p \tag{6}$$

Where $V_{it}$ denotes the log first difference of the price change in stock i at time t, with i = 1, ..,N and t = 1,..,T. We impose equal probability levels across all bank and property stocks for reasons of comparability and parsimony. However, the crash levels $Q_i$ will in general have different values, as the marginal probability distribution functions $P\{V_{it} > Q_i\} = 1 - F(Q_i)$ are stock specific. Further we define distress level return $Q_i^* < Q_i$ such that any excess return is seen as a sign of extreme distress, albeit not necessarily a crash. The probability of variable $V_i$ exceeding tail value $Q_i^*$ is defined as equal to $P\{V_{it} > Q_i^*\} = \lambda P\{V_{it} > Q_i\} = \lambda p$ . Because we use daily data, each stock will, on average, exceed its crash level $Q_i$ only once in every 1/p days and its distress level $Q_i^*$ once in every $\lambda / p$ days. We derive the conditional distress (CD)-probability in stock i (for example a bank) given that stock m (for example a property firm) crashes as:

$$CD \equiv P\{V_{it} > Q_i^* | V_{mt} > Q_m\} = \frac{P\{(V_{it} > Q_i^*) \cap (V_{mt} > Q_m)\}}{P\{V_{mt} > Q_m\}}$$

$$= \frac{P\{V_{it} > Q_i^*\} + P\{V_{mt} > Q_m\} - P\{(V_{it} > Q_i^*) \cup (V_{mt} > Q_m)\}}{P\{V_{mt} > Q_m\}}$$

$$= \frac{(\lambda + 1)p - P\{(V_{it} > Q_i^*) \cup (V_{mt} > Q_m)\}}{p} \tag{7}$$

We refer to Zhang and Shinki (2007) who also use a probability-based EVT approach to measure extreme co-movements and extreme impacts in an application on foreign exchange spot rates. The CD-probability in equation (7) may be estimated by a non-parametric count measure:

$$CD = (\lambda + 1) - \frac{1}{k} \sum_{t=1}^{T} I\{V_{it} > x_{i,T-\lambda k}, or V_{mt} > x_{m,T-k}\} \tag{8}$$

in which I stands for the indicator function, $x_{i,T-\lambda k}$ and $x_{m,T-k}$ are the λk-th and k-th highest order statistics of stocks i and m respectively. Essentially, one counts the instances at which either one or both stocks experience an extreme return. For consistency reasons, we use the same value of threshold k in multivariate equation (8) as in univariate equation (2). We refer to Coles et al. (1999, p. 346) who use a similar estimation method to calculate extreme dependence probabilities. Moreover, the CCC-probability used in Hartmann et al. (2004) is a special case of the CD-probability defined in equation (7) as it is obtained by setting the multiplicator parameter λ equal to 1. The CCC-probability thus measures the likelihood of a stock crashing given that another one crashes. We mostly employ these CCC-probabilities throughout this paper, although we also calculate CD-probabilities when we study extremal sector dependencies in sector 7.

## 4. Data Description

Our sample is selected from the Datastream list of the 55 largest exchange-listed financials in Australia and New Zealand (Datastream mnemonic "G#LFINANAZ"). A total of seven Australian banks are included in this list. There are no New Zealand exchange-listed banks available. We classify a security as part of the property sector if its main activities concern property. Regular investment managers, insurance companies and the exchange itself are removed. The sample of property securities includes both trusts and corporations that are active in development, investment and management of residential, commercial, retail, industrial and hotel properties. For reasons of brevity, we refer to all the property securities as property firms. Most of the property firms are located in either Australia or New Zealand, but some have large international activities and investments as well. The value of the real estate under management is significant and for several firms exceeds A$10 billion. We only include those series for which we deem daily trading volume sufficiently high to have minimal illiquidity problems in the price formation, for example bid-ask bounces or price gaps. A number of property firms are removed because trading volumes are too low. Further, as the starting date we take 05/01/2000 because for one property firm the stock price is available only after this date. All series end at 06/02/2009. In order to prevent cross-sectional comparability problems due to scale differences, we use only those series for which the whole period between 05/01/2000 and 06/02/2009 is available, which amounts to 2372 observations per series. As a result of the above selection criteria, the property sector within the data sample is reduced to a total of nine Australian property securities and four New Zealand property securities. In total we have 20 individual series for which total return indices were obtained from Datastream. Finally, in order to also study sectoral tail dependencies, we include an Australian banking index ("BANKSAU") and an Australian real estate index ("RLESTAU"), as well as 11 other Datastream sector indices for the same data period and frequency as the individual series.

### *4.1 Data Summary Statistics*

In Table 1 we show the summary statistics of all returns series, which are calculated as the natural logarithms of the first differences of the original Datastream total return indices.

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Table 1 shows that over the full nine-year sample period Australian banks have on average outperformed the Australian property firms. All banks exhibit positive average returns. Per contrast, four property firms have negative average returns. Moreover, the bank index return average is positive and exceeds the property index average. In spite of these differences, the two indices show very similar behavior over time, as is depicted in Figure 1.

> PLACE FIGURE 1 AROUND HERE <

The four New Zealand property firms stand out because of their relatively high positive returns, hence on average outperforming their Australian counterparts. Further, the New Zealand property firms are less volatile than both the Australian banks and the Australian property firms, as is evidenced by other summary statistics in Table 1. Most of their minimum and maximum returns are lower (in an absolute sense) than those of the other return series. They also show relatively low standard deviations and kurtosis levels. Moreover, the Australian property firms show higher standard deviations and kurtosis levels than the Australian banks, as well as more negative skews. Nearly all series show a kurtosis higher than three, which means that the return distributions have fat tails which is in line with Jansen and de Vries (1991) and Poon et al. (2004). All series thus show a relatively high likelihood of generating a large loss, as compared to a standard normal distribution. In the next section we estimate these likelihoods.

**5. Univariate Risks**

In this section we analyze the probability that a large negative return will occur. We first employ the Hill-estimator of equation (2) to determine the best empirical approximation of the fatness of the left tails. Following Straetmans et al. (2008) and Slijkerman et al. (2005, p. 29) we construct so-called Hill-plots for all series, which show the relationship between the number of order statistics used (k), and the tail index estimate $\hat{\gamma}(k)$. As an illustration, a sample of four Hill-plots is included in Appendix I. We use the Hill-plots to determine the optimal level of k, which depends on the sample size and the tail thickness; the further one moves out into the tails, the better becomes the Pareto approximation of these tails. As a counterforce, the estimate begins to be based on fewer observations and thus more uncertain. If the number of observations is increased too much, the statistical power increases but the estimate of the tail becomes distorted. In practice, a balance between the two opposing effects needs to be struck. Visual inspection of the Hill-plots is needed to determine a range for k where $\hat{\gamma}(k)$ tends to be constant. For the full sample period we set the number of order statistics used equal to fifty, as at this level the Hill-estimators are relatively stable. This threshold level compares nicely to the fifty order statistics used by Slijkerman et al. (2005) on a similar data sample size as well as the two percent threshold level used by Poon et al. (2004, p. 593).

In order to analyze whether or not the distribution of the extremes has changed, we need to determine a breakpoint. We choose the starting date of the credit crisis to be 1 May 2007. This breakpoint is just prior to the June 2007 period when two large Bear Stearns hedge funds that were dealing in mortgages ran into serious trouble. The crash in these hedge funds was one of the first large events to indicate the advent of the credit crisis. For the pre-crisis period and the crisis period itself we use 40 and 20 order statistics respectively, thus striking a balance between using enough observations and limiting the selection to the most extreme events only. As a robustness test we varied the number of order statistics used and found that moderate changes do not significantly affect the key results. Table 2 depicts the Hill-estimators and 95 percent-confidence intervals of all the series' left tails for the full sample period as well as for the pre-crisis and crisis periods.

> PLACE TABLE 2 AROUND HERE <

Table 2 shows that most Hill-estimators vary between two and four, which is in line with the results in Hartmann et al. (2006). Further, the Australian property firms show fatter left tails than do the banks, as is evidenced by the lower Hill-estimates. This finding is in line with the higher kurtosis of the property firms reported in Table 1. Evidently, over the past decade, extreme tail risks for investing in Australian property firms were higher than for investments in Australian banks. From Table 2 we further conclude that most property firms had higher tail parameters before the credit crisis, thus reflecting thinner tails. However, for banks the picture is mixed, as some banks have thinner tails after 1 May 2007 and most of the changes are statistically insignificant. The first results indicate that the property sector seems to have been hit harder than the banking sector, as is evidenced by the larger fall in the tail index estimate for the property sector. This conclusion is supported by the changes in the kurtosis and by Figure 1. Table 2 also shows that in some cases the tail parameter estimate of the full sample comes out lower than the estimate for each of the two subperiods individually. The non-linear tail shape parameter estimate of the full sample is not a weighted average of the subperiods' estimates.

Because the tail parameters do not translate directly into financial distress risks, we also calculate 99.9 percent VaR and ES for all series and report these measures in Table 3.

> PLACE TABLE 3 AROUND HERE <

Table 3 shows that after 1 May 2007 for all series the 99.9 percent VaR and ES have increased with the exception of two New Zealand property firms. Prior to the credit crisis the averages of the 99.9 percent VaR and ES measures for banks (6.00 percent and 8.61 percent) and Australian property firms (6.02 percent and 8.28 percent) were very similar. During the credit crisis the left tails of the property firm distribution were affected more and the banks proved relatively stable, as evidenced by lower VaR and ES estimates both during the credit crisis as well as over the full sample period. All in all, our calculations show that the tail risks have increased for both sectors, but that the property sector was more affected by the credit crisis.

## 6. Contagion Risks

Next, we calculate the CCC-probabilities of observing joint meltdowns in bank and property stock prices. Multivariate EVT enables us to investigate whether the financial crisis has increased the tail dependency between the Australian banking and property sectors. It would be intuitive to assume that the co-movements have become more prominent. The estimated CCC-probabilities are shown in the tables below.

> PLACE TABLES 4 - 7 AROUND HERE <

A first conclusion from Table 4 is that the CCC-probabilities of the New Zealand property firms are remarkably low, as they range between 0 percent and 14 percent only. Apparently, the market perceives the extremal link between the New Zealand property firms and the Australian banks or property firms to be rather weak. In order to understand this finding, we inspected the individual annual reports of the four New Zealand property firms in our sample. The outstanding debt of all four companies is fully (for three) or nearly fully (for one) financed by the four Australian pillar banks or their New Zealand subsidiaries. There are no foreign banks involved in any of these loans. Most of the four New Zealand property firms have in place further credit lines with the same banks; the amounts outstanding are substantial and vary between \$100 million and \$750 million per end of 2008. Moreover, in 2008 and 2009 several of these property firms have been going through a recapitalization process by means of rights issues and other placements. Further equity raisings are foreseen in the New Zealand property sector.

The existing levels of debt and additionally available credit lines suggest the presence of a strong link between the banks and the property firms. However, probably the most relevant observation is that the gearing ratios (the level of debt over tangible assets) are lower than 30 percent for all four property firms. The equity raisings have kept the gearing levels at fairly low rates and have largely counterbalanced the devaluations of the real estate assets on the balance sheet. As a consequence, under the assumption that the banks have first mortgage on the underlying assets, the banks' risks still quite low. Property prices would have to fall by unprecedented percentages before the banks' loans are endangered. These relatively conservative gearing ratios may explain the above finding in which there appears to be no material link between Australian banks' and New Zealand property firms' extremal share price returns.

Secondly, we glean from Table 4 that in Australia the intra-property-sector CCC-probabilities are markedly higher than is the case in New Zealand. There is for example a 52 percent probability of a crash in Dexus occurring if the Stockland shares fall strongly. Interestingly, the CCC-probability between GPT and Stockland equals around 48 percent, which exceeds the intra-sector average of 36 percent. This already elevated CCC-probability may rise even further in the future, as in November 2008 Stockland bought a 12.7 percent stake in GPT. The estimated tail behavior informs us that the two firms were already regarded as strongly linked even prior to the acquisition. Moreover, Stockland has a relatively high average tail dependency with both the banks and the property securities.

Thirdly, the CCC-probabilities between the Australian property securities and banks are quite high as well. The lowest CCC-probability is found between Dexus and Bank of Queensland at 14 percent. There indeed is no evidence of an obvious link between these two firms. Per contrast, there is a 40 percent likelihood of a crash in the shares of ANZ if either Stockland's or Westfield's shares fall drastically. Both Stockland and Westfield are large property firms: Stockland has total assets of nearly \$15 billion per 2008. Westfield has \$29 billion of real estate assets in Australia and \$3 billion in New Zealand, which together comprise 46 percent of its total assets with the remainder in the US and the UK. The majority of both Stockland's and Westfield's financing is sourced through Medium Term Notes rather than through bank loans. The direct interdependence between Stockland and the banking sector thus of lesser relevance. However, Stockland's results largely depend on Australian residential real estate, with 80 percent of its 2008 revenues generated by this sector. As the banks' results are highly dependent on the wellbeing of this same sector, it is no surprise that the earnings of Stockland may be interpreted as an indicator for the banks' results. This shared dependence on residential real estate could explain the elevated CCC-probabilities between Stockland and the banking sector.

Moreover, from Table 4 we glean that the four pillar banks (ANZ, CBA, NAB and Westpac) are relatively strongly linked. The probability of one pillar bank crashing simultaneously with another pillar bank falling over averages 44 percent over the full sample period (and 30 percent during the pre-crisis period, which is calculated from Table 5). In such an unfortunate scenario it seems likely that the other banks will come under great pressure as well and more bank failures become likely if the regulators do not intervene. Per contrast, the average CCC-probability of the other banks, in which case at most one Australian pillar bank crashes, equals a lower 32 percent (or 14 percent prior to the crisis). Apparently the market recognizes that the four pillar banks are strongly connected when disaster strikes. Our results suggest that if one of the pillars falls it could easily lead to a systemic crash. This finding supports the notion that the "too big to fail" doctrine applies to the four pillar banks.

Further, with regard to the inter-sector contagion risks, we identify several direct links between the property firms and banks. One example of this is seen when a bank owns shares in a property fund or if a bank has a client referral scheme with a property fund. Another example is the case of the Macquarie Bank and Macquarie Office Trust. Both securities partially the same name and the bank exercises general oversight and provides many services to the fund (see the Macquarie Office Trust annual report of 2008, p. 34 for more details). Macquarie Office Trust is operating with a 45 percent gearing ratio and more than half its borrowings consist of bank debt. However we find no evidence of a relatively stronger link in times of extreme distress. The CCC-probability in Table 4 equals 30 percent, which is close to the average 27 percent CCC-probability between the bank and property shares as shown in Table 7.

Table 7 also shows that the average intra-sector CCC-probability is nearly the same across the two sectors at 36 percent for the banks and 38 percent for the property sector, and it exceeds the average inter-sector probability at 27 percent. Finally, Table 7 shows that the CCC-probabilities were markedly lower, on average, prior to the credit crisis. Apparently, the extremal dependency has increased. The intra-sector CCC-probabilities have moved from averages of 19 percent and 14 percent for the bank and property sectors, to 38 percent and 36 percent respectively for the full period. The average CCC-probability between the property and banking sector equalled only 6 percent before the crisis, but has advanced markedly to 27 percent in the full sample period.

## 7. Extremal Sector Dependence

As we discussed in sections 1 and 2, an extensive body of literature emphasizes the strong relationship between the banking and property sectors, specifically the relevance of a shock to the real estate market as a leading indicator of an upcoming banking crisis. Following this line of thought, the previous sections show that during the credit crisis the VaR and ES risk measures of both the banking and property sectors have increased. Moreover, both the extremal intra-sector and inter-sector dependencies have also increased markedly.

However, none of these findings establishes whether the crash in the property sector is more important to the banking sector than to other sectors in the economy (summary statistics of the sector returns are given in Appendix III). Banks fulfil a special role in the economy as they provide financial services to all industries; therefore, one could argue that the banks' performance depends on the performance of all sectors and that the property sector is only one of many which influence the banks' returns. To further explore this issue, the CCC-probabilities of all sectors and the banking sector are reported in Table 8.

> PLACE TABLE 8 AROUND HERE <

From Table 8 we glean that of all 13 sectors analyzed, the property sector exhibits the highest level of extremal dependence with the banking sector. For four sectors the difference in CCC-probability with the banking sector is significant at either the one percent, five percent or ten percent level. For all other sectors, except one, the difference is significant at the 15 percent level. Interestingly, this picture has emerged only recently. Before the crisis five other sectors showed higher or equal CCC-probabilities with the banking sector, although the differences were all insignificant at the 10 percent level. The financial crisis has made the extremal dependence of the banks on the property sector more evident with rising CCC-probabilities from 0.18 to 0.36, the same as has occurred before in other countries and other financial crises.

Additionally, we study the other (non-crash) parts of the distribution tails because they carry relevant information as well. For example, a crash in the property index may coincide relatively often with a very large negative return in the banking index. Although not necessarily a full-fledged crash, such a strongly negative return still reflects a high degree of distress. A measurement of the relative frequency of occurrence of such extreme conditional returns assesses the extremal dependence between the two sectors and can be used simultaneously with the CCC-probabilities. The conditional distress (CD) probability is defined in equation (8) as the likelihood that a crash in one sector (e.g. property) coincides with an extreme return in another sector (e.g. banking). As stated elsewhere in this paper, we assume that for the full sample period the 50 most negative returns represent crash-like events, i.e. 2.1 percent of all observations. We assume that the $\lambda$ * 50 most negative returns are seen as extreme distress events. We set the multiplicator $\lambda$ equal to 3, thus use the most negative 150 returns, i.e. 6.3 percent of all observations. This distress level is still close to the conventional 5 percent VaR level often used in practice. Our unreported results show that our main conclusions are robust to changes in the multiplicator $\lambda$ between 1 and 5. Figure 2 shows the pre-crisis and full-period CD-probability of an extreme return in each sector, conditional on the occurrence of a crash in the property sector.

> PLACE FIGURE 2 AROUND HERE <

Figure 2 reveals that the CD-probability for the banking sector, conditional on a crash in the property sector, markedly exceeds those for all other sectors. For the full sample period approximately 74 percent of all crash-like property sector returns coincide with a distressed banking sector return. For the other sectors this percentage does not exceed 56 percent. Moreover, the CD-probability for the banking sector has increased from 30 percent to 74 percent during the credit crisis, which is more than in any of the other sectors. Our findings thus provide strong empirical evidence for the relative importance that the property sector carries for the stability of the banking sector.

## 8. Conclusion

One of the most significant features of the recent global financial crisis has been how quickly it has spread over the entire world. The reason which both justifies and underscores the importance of analyzing Australian banks is that they have yet to experience substantial losses related with the current global crisis, and in particular with their real estate lending; this is the case despite declining profitability and increasing problem loans related to that sector.

The Reserve Bank of Australia (Financial Stability Review 2009) argues that the relatively good results of Australian banks are a consequence of their proactive stance on prudential regulation and tougher lending standards than those seen in the US. Accordingly, the motivation for preparing this paper lies in assessing whether Australian banks have truly been immune to the crisis both individually and collectively through contagion risk. This paper estimated three types of risks:

- 1. if the probability of large individual negative returns has increased since the outbreak of the crisis (univariate risks)
- 2. if contagion risk has increased with the recent global crisis (intra-sector contagion)
- 3. if contagion risk is related to the crash experienced in the real estate markets both in Australia and New Zealand where Australian banks dominate the sector (inter-sector contagion)

The results indicate that the risk of extreme spillovers as measured by the CCC-probabilities is quite high between the Australian property securities and the banks, but not so much between the New Zealand property securities and the banks. Further investigation reveals that the Australian banks' exposure to the New Zealand real estate sector through their New Zealand subsidiaries is less relevant, possibly because New Zealand property firms operate with lower levels of leverage than their Australian counterparts and therefore their loans are less risky. Our results also show that investors understand the common risks faced by property firms and banks due either to banks' direct loans to some property firms or because both sectors are jointly exposed to a downturn in the real estate market.

The recent crisis has increased both the dependences within the sectors, especially within the property sector, and also the inter-sector dependence, with the average CCC-probability or risk of contagion between the property and banking sector advancing from 7 percent to 27 percent. We also found that the conditional distress probability, which measures the likelihood that a crash in the property sector will be followed by a large negative return in another sector, was much higher for the banking sector than for any other sector. The current crisis has markedly increased banking system risk (the interdependence within the banking sector has gone from 14 percent to 36 percent) and the risk of wider bank problems resulting from a common shock to the real estate sector has become more likely as both countries continue to work their way through the crisis.

These results have important policy implications. Historically, banking crises around the world have often been preceded by a lending boom which results in an asset market bubble in the real estate market; when the bubble bursts, the unsustainable levels of debt for the household and non-household sectors and the sharp drop in asset values cause a series of problems for banks. If a global financial crisis such as the current one cannot be avoided, it is important that supervisory authorities at least understand where the system is most vulnerable.

Over the last ten years APRA's approach to supervision has moved to a "risk-based supervision" model implemented through PAIRS; this means that the regulatory attention is focused on the institutions whose activities generate the greatest risk or pose the largest systemic risk. APRA's measurement of systemic risk is based on one single figure, the total resident Australian assets (Laker 2007). However, this number does not reveal anything regarding how the risk is spread through the system or where it comes from. Our results suggest that the contagion risk stemming from the property sector is the most relevant for the banks and deserves close attention from the supervisors. Within the banking sector, the four pillar banks are relatively strongly linked in times of crisis and the failure of one of the pillars could easily lead to a full-blown systemic crisis. The notion that under Pillar II of Basel II banks may be required to have an extra capital buffer for contagion risk appears most appropriate for the four Australian pillar banks in order to weather property sector contagion risks and intra-sector spillover effects.

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Figure 1. Australian bank and property indices developments

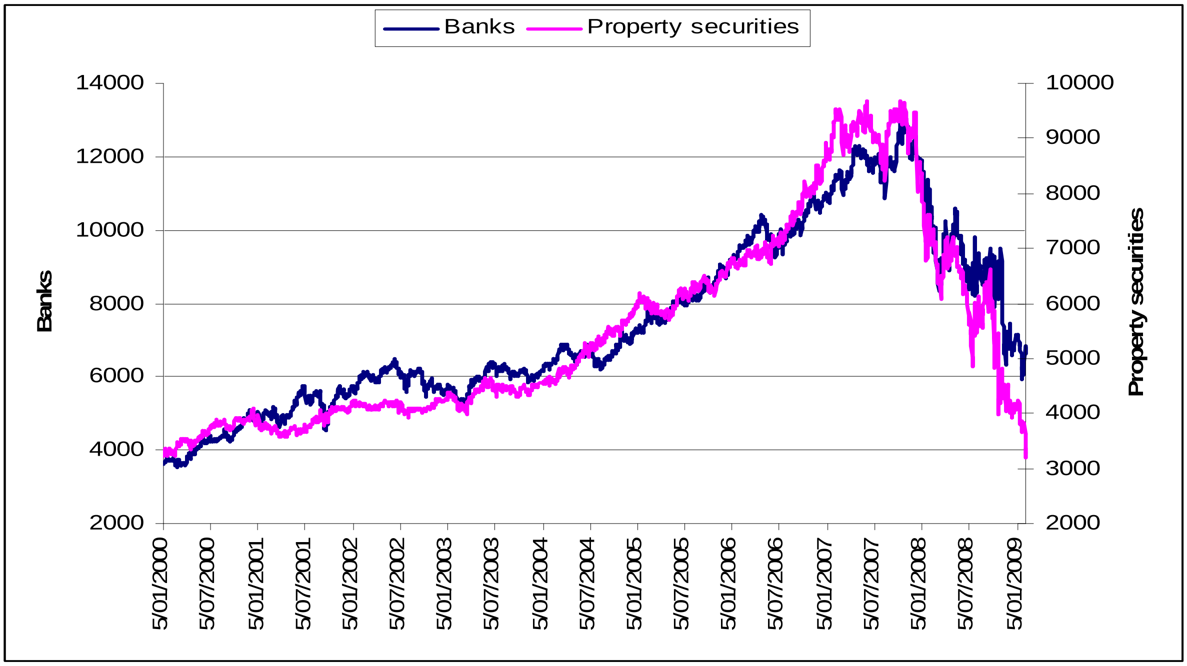


Figure 1 depicts total return indices for the banking and property sectors across the full sample period.

Figure 2. Conditional distress probabilities for all sectors upon a crash in the property sector

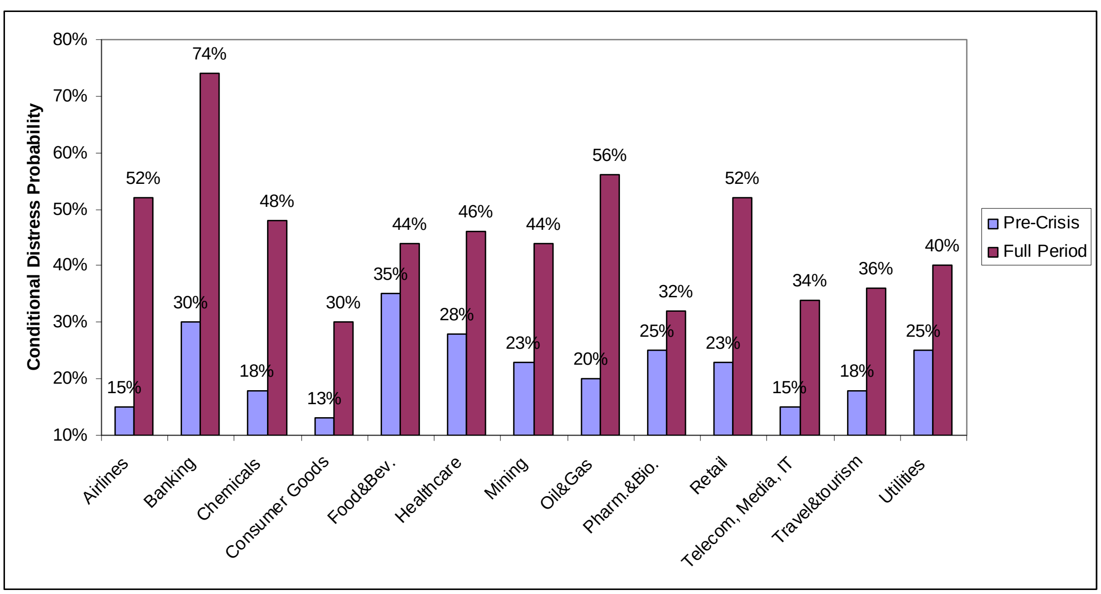


Figure 2 depicts conditional distress probability estimates based on equation (8) with multiplicator $\lambda$=3. For each sector it measures the likelihood of distress (defined as the 6.3% lowest returns) occurring jointly with a crash in the property sector (defined as the lowest 2.1% returns). These probabilities are depicted for the full sample period of 05/01/2000 – 06/02/2009 and for the pre-crisis period of 05/01/2000 – 30/4/2007.

Table 1. Summary statistics of share price return series

| | Avg. | Min. | Max. | St.dev. | Skew | Kurt. |
|---|---|---|---|---|---|---|
| ASX-listed Property | | | | | | |
| Commonwealth Property | 0.019% | -13.04% | 14.25% | 1.66% | 0.02 | 14.33 |
| Dexus Property Group | 0.007% | -26.14% | 10.69% | 1.89% | -1.62 | 23.83 |
| Goodman Group | 0.054% | -29.70% | 20.50% | 2.97% | -0.87 | 13.20 |
| GPT Group | -0.023% | -31.29% | 14.16% | 1.98% | -2.22 | 39.64 |
| ING Office Fund | -0.027% | -19.56% | 13.70% | 2.02% | -2.00 | 23.12 |
| Macquarie Office Trust | -0.041% | -41.78% | 34.30% | 2.52% | -1.05 | 62.68 |
| Mirvac | -0.019% | -26.45% | 30.04% | 2.11% | -0.44 | 41.79 |
| Stockland | 0.024% | -11.23% | 9.57% | 1.70% | -0.67 | 10.37 |
| Westfield Group | 0.020% | -13.20% | 20.92% | 1.80% | 0.51 | 13.10 |
| NZX-listed Property | | | | | | |
| AMP NZ Office Trust | 0.033% | -9.31% | 9.20% | 1.29% | 0.05 | 5.43 |
| Goodman Property Trust | 0.036% | -13.23% | 6.58% | 1.23% | -0.41 | 8.67 |
| Kiwi Income Property Trust | 0.031% | -7.02% | 6.90% | 1.11% | -0.22 | 3.34 |
| Property for Industry | 0.043% | -5.36% | 6.90% | 1.26% | 0.15 | 1.60 |
| Banks | | | | | | |
| AU & NZ Banking Group | 0.028% | -11.54% | 13.68% | 1.61% | 0.04 | 10.45 |
| Bank of Queensland | 0.033% | -10.24% | 12.00% | 1.69% | -0.14 | 5.58 |
| Bendigo & Adelaide Bank | 0.043% | -11.16% | 25.52% | 1.85% | 1.62 | 21.92 |
| Commonwealth Bank of AU | 0.026% | -9.53% | 11.79% | 1.45% | 0.00 | 7.63 |
| Macquarie Group | 0.012% | -26.38% | 32.11% | 2.38% | 0.20 | 25.75 |
| National Australia Bank | 0.012% | -14.46% | 16.03% | 1.67% | -0.51 | 12.64 |
| Westpac Banking | 0.039% | -11.79% | 8.61% | 1.52% | -0.06 | 6.08 |
| Indices | | | | | | |
| Banks | 0.025% | -8.49% | 9.69% | 1.31% | 0.13 | 8.06 |
| Property | 0.000% | -11.57% | 8.03% | 1.30% | -1.25 | 14.75 |

Table 1 reports the summary statistics of the natural logarithms of the first differences of all 22 Datastream daily total return indices over the full sample period 05/01/2000 – 06/02/2009. Columns two, three and four report the average, minimum and maximum returns. Columns five, six and seven report the standard deviation, skew and kurtosis of the return distribution.

Table 2. Left tail index estimates

| | | Full Sample Period | Pre-Crisis Period | Crisis Period | T-Test |
|---|---|---|---|---|---|
| AU Property Firms | Commonwealth Property | 2.48 (2.14, 3.86) | 2.85 (2.34, 3.87) | 3.57 (2.30, 6.15) | 0.84 |
| | Dexus Property Group | 2.11 (1.72, 2.90) | 5.03 (3.42, 6.91) | 2.47 (1.78, 4.25) | 2.10** |
| | Goodman Group | 2.32 (1.81, 3.12) | 2.56 (2.05, 3.69) | 2.43 (1.73, 4.43) | 0.12 |
| | GPT Group | 2.02 (1.67, 2.95) | 4.46 (3.42, 6.40) | 2.60 (1.90, 4.70) | 1.66** |
| | ING Office Fund | 2.02 (1.48, 2.82) | 4.57 (2.87, 7.53) | 1.95 (1.87, 3.92) | 1.76** |
| | Macquarie Office Trust | 1.72 (1.33, 2.55) | 3.82 (2.37, 6.15) | 3.04 (1.87, 5.36) | 0.66 |
| | Mirvac | 1.58 (1.39, 2.55) | 3.94 (2.49, 6.70) | 2.06 (1.78, 4.95) | 0.94 |
| | Stockland | 2.20 (1.91, 2.98) | 3.46 (2.78, 4.59) | 3.30 (2.27, 8.60) | 0.32 |
| | Westfield Group | 2.87 (2.31, 4.05) | 3.91 (3.17, 5.47) | 3.17 (2.21, 5.22) | 0.55 |
| | Avg. AU Property Firms | 2.15 | 3.84 | 3.31 | |
| NZ Propert y Firms | AMP NZ Office Trust | 2.44 (1.96, 3.69) | 2.34 (1.80, 3.86) | 2.96 (2.13, 5.52) | 0.70 |
| | Goodman Property Trust | 3.19 (2.56, 4.75) | 3.09 (2.16, 4.62) | 3.02 (2.13, 4.89) | 0.01 |
| | Kiwi Income Property Trust | 3.04 (2.52, 4.20) | 4.02 (2.87, 5.66) | 2.75 (2.00, 4.27) | 1.05 |
| | Property for Industry | 4.32 (3.65, 5.92) | 4.12 (3.19, 5.55) | 3.96 (3.13, 6.93) | 0.23 |
| | Avg. NZ Property Firms | 3.25 | 3.39 | 4.25 | |
| Banks | AU & NZ Banking Group | 3.13 (2.38, 4.11) | 4.63 (3.34, 6.59) | 3.16 (2.07, 5.41) | 1.39* |
| | Bank of Queensland | 3.48 (2.62, 4.62) | 3.89 (2.82, 5.37) | 3.45 (2.52, 5.00) | 0.43 |
| | Bendigo & Adelaide Bank | 3.64 (2.90, 4.47) | 3.78 (3.21, 5.84) | 5.26 (3.31, 9.24) | 0.79 |
| | Commonwealth Bank of AU | 2.50 (1.97, 3.51) | 3.77 (2.94, 5.69) | 3.28 (2.44, 7.69) | 0.02 |
| | Macquarie Group | 2.50 (1.97, 3.22) | 3.34 (2.35, 4.73) | 3.18 (2.29, 6.79) | 0.18 |
| | National Australia Bank | 2.82 (2.19, 4.06) | 3.00 (2.01, 4.80) | 3.46 (2.18, 6.94) | 0.50 |
| | Westpac Banking | 3.39 (2.54, 5.07) | 4.44 (3.46, 5.92) | 3.13 (2.41, 5.11) | 1.13 |
| | Average Banks | 3.07 | 3.84 | 4.33 | |
| Indices | Banks | 2.88 (2.41, 4.93) | 3.79 (2.66, 5.47) | 4.97 (3.25, 8.63) | 0.82 |
| | Property Firms | 2.24 (1.57, 2.93) | 3.90 (2.66, 5.39) | 3.51 (2.11, 5.45) | 0.44 |

Table 2 reports Hill estimates of the left tails of the return probability distribution functions based on equation (2). The periods 05/01/2000 – 06/02/2007 (full sample period), 05/01/2000 – 30/04/2007 (pre-crisis period) and 01/05/2007 – 06/02/2009 (crisis period) are distinguished. For these periods we use 50, 40 and 20 order statistics k respectively. We have sorted the 600 block bootstrapped simulations of the tail estimates and used the 15-th and

585-th estimate to generate 95 percent confidence intervals which are reported in parentheses. The last column reports the T-test of equation (3) to determine if the tail index has decreased significantly during the credit crisis. The superscripts *, **, *** denote significance at the ten percent, five percent, and one percent level respectively.

Table 3. Univariate extreme risk measures

| | Full Sample Period | | Pre-Crisis Period | | Crisis Period | |
|---|---|---|---|---|---|---|
| | 99.9% VaR | 99.9% ES | 99.9% VaR | 99.9% ES | 99.9% VaR | 99.9% ES |
| AU Property Securities | | | | | | |
| Commonwealth Property | 12.82% | 21.49% | 6.51% | 10.02% | 16.34% | 22.70% |
| Dexus Property Group | 16.70% | 31.73% | 4.46% | 5.57% | 28.35% | 47.64% |
| Goodman Group | 24.02% | 42.27% | 14.25% | 23.37% | 39.86% | 67.73% |
| GPT Group | 18.99% | 37.68% | 4.02% | 5.18% | 29.09% | 47.27% |
| ING Office Fund | 20.82% | 41.15% | 4.32% | 5.53% | 48.77% | 100.00% |
| Macquarie Office Trust | 29.58% | 70.69% | 4.97% | 6.73% | 33.72% | 50.25% |
| Mirvac | 27.78% | 75.92% | 4.39% | 5.88% | 44.12% | 85.74% |
| Stockland | 15.74% | 28.90% | 4.83% | 6.79% | 19.96% | 28.64% |
| Westfield Group | 10.95% | 16.82% | 6.29% | 8.44% | 16.96% | 24.78% |
| Avg. AU Property Securities | 19.71% | 40.74% | 6.00% | 8.61% | 30.80% | 52.76% |
| NZ Property Securities | | | | | | |
| AMP NZ Office Trust | 8.48% | 14.37% | 8.80% | 15.35% | 7.29% | 11.01% |
| Goodman Property Trust | 6.88% | 10.02% | 6.56% | 9.70% | 8.72% | 13.04% |
| Kiwi Income Property Trust | 6.18% | 9.22% | 4.54% | 6.04% | 9.41% | 14.79% |
| Property for Industry | 5.26% | 6.84% | 5.11% | 6.74% | 6.39% | 8.55% |
| Avg. NZ Property Securities | 6.70% | 10.11% | 6.25% | 9.46% | 7.85% | 11.85% |
| Banks | | | | | | |
| AU & NZ Banking Group | 9.68% | 14.22% | 4.89% | 6.23% | 16.30% | 23.85% |
| Bank of Queensland | 9.53% | 13.38% | 6.30% | 8.48% | 15.10% | 21.26% |
| Bendigo & Adelaide Bank | 8.94% | 12.32% | 6.35% | 8.63% | 10.28% | 12.69% |
| Commonwealth Bank of AU | 10.49% | 17.47% | 4.95% | 6.73% | 14.04% | 20.20% |
| Macquarie Group | 18.01% | 30.03% | 8.37% | 11.95% | 25.02% | 36.50% |
| National Australia Bank | 11.14% | 17.24% | 6.70% | 10.05% | 14.44% | 20.31% |
| Westpac Banking | 8.10% | 11.48% | 4.57% | 5.90% | 14.06% | 20.66% |
| Average Banks | 10.84% | 16.59% | 6.02% | 8.28% | 15.61% | 22.21% |
| Indices | | | | | | |
| Banks | 7.98% | 11.50% | 4.07% | 5.53% | 9.09% | 11.38% |
| Property | 11.96% | 21.35% | 3.02% | 4.07% | 15.23% | 21.30% |

Table 3 reports Value-at-Risk and Expected Shortfall estimates based on equations (4) and (5) for all 22 series for the periods 05/01/2000 – 06/02/2009 (full sample period), 05/01/2000 – 30/04/2007 (pre-crisis period) and 01/05/2007 – 06/02/2009 (crisis period).

Table 4. Conditional-co-crash probabilities for the full sample period

| | Com. Wealth | Dexus | Goodman | GPT | ING Office | Macquarie office | Mirvac | Stockland | Westfield | Average of row |
|---|---|---|---|---|---|---|---|---|---|---|
| ASX-listed Property | | | | | | | | | | |
| Dexus Property Group | 30% | | | | | | | | | |
| Goodman Group | 14% | 36% | | | | | | | | |
| GPT Group | 30% | 42% | 32% | | | | | | | |
| ING Office Fund | 36% | 46% | 30% | 38% | | | | | | |
| Macquarie Office Trust | 40% | 46% | 28% | 42% | 44% | | | | | |
| Mirvac | 28% | 46% | 34% | 50% | 36% | 38% | | | | |
| Stockland | 38% | 52% | 38% | 48% | 40% | 44% | 50% | | | |
| Westfield Group | 30% | 32% | 36% | 36% | 28% | 36% | 30% | 50% | | |
| NZX-listed Property | | | | | | | | | | |
| AMP NZ Office Trust | 8% | 14% | 8% | 10% | 14% | 12% | 14% | 12% | 8% | 11% |
| Goodman Property Trust | 6% | 10% | 6% | 8% | 8% | 6% | 12% | 12% | 8% | 8% |
| Kiwi Income Property Trust | 8% | 12% | 8% | 6% | 14% | 10% | 12% | 8% | 10% | 10% |
| Property for Industry | 0% | 4% | 8% | 6% | 2% | 8% | 6% | 4% | 10% | 5% |
| Banks | | | | | | | | | | |
| AU & NZ Banking Group | 24% | 26% | 28% | 32% | 36% | 30% | 34% | 40% | 40% | 32% |
| Bank of Queensland | 22% | 14% | 18% | 32% | 22% | 22% | 24% | 26% | 22% | 22% |
| Bendigo & Adelaide Bank | 18% | 18% | 18% | 28% | 22% | 16% | 28% | 26% | 26% | 22% |
| Commonwealth Bank of AU | 26% | 24% | 24% | 30% | 24% | 30% | 26% | 36% | 30% | 28% |
| Macquarie Group | 30% | 24% | 20% | 38% | 32% | 30% | 28% | 34% | 30% | 30% |
| National Australia Bank | 26% | 24% | 24% | 34% | 28% | 26% | 34% | 30% | 32% | 29% |
| Westpac Banking | 20% | 28% | 24% | 24% | 28% | 28% | 24% | 34% | 24% | 26% |
| Indices | | | | | | | | | | |
| Bank-index | 28% | 266% | 26% | 32% | 30% | 28% | 28% | 38% | 32% | % |
| Property-index | 46% | 56% | 44% | 54% | 50% | 56% | 52% | 70% | 60% | % |

Table 4. Conditional-co-crash probabilities for the full sample period

| | ANZ | Bank of Queensland | Bndigo & Adelaide | CBA | Macquarie | NAB | Westpac | Bank-index | Property-index |
|---|---|---|---|---|---|---|---|---|---|
| NZX-listed Property | | | | | | | | | |
| AMP NZ Office Trust | 8% | 4% | 4% | 4% | 6% | 6% | 12% | 8% | 10% |
| Goodman Property Trust | 12% | 12% | 8% | 10% | 10% | 8% | 6% | 10% | 12% |
| Kiwi Income Property Trust | 10% | 8% | 6% | 10% | 14% | 10% | 10% | 8% | 8% |
| Property for Industry | 8% | 6% | 12% | 10% | 10% | 10% | 6% | 10% | 10% |
| Banks | | | | | | | | | |
| AU & NZ Banking Group | | | | | | | | 54% | 32% |
| Bank of Queensland | 28% | | | | | | | 32% | 32% |
| Bendigo & Adelaide Bank | 40% | 28% | | | | | | 40% | 34% |
| Commonwealth Bank of AU | 42% | 26% | 36% | | | | | 54% | 34% |
| Macquarie Group | 32% | 32% | 36% | 36% | | | | 38% | 38% |
| National Australia Bank | 54% | 30% | 42% | 48% | 38% | | | 58% | 32% |
| Westpac Banking | 42% | 22% | 30% | 40% | 28% | 38% | | 42% | 30% |
| Indices | | | | | | | | | |
| Bank-index | 60% | 32% | 50% | 72% | 44% | 70% | 54% | | |
| Property-index | 42% | 28% | 30% | 32% | 40% | 32% | 36% | 36% | |

Table 4 reports conditional-co-crash probability estimates based on equation (7) for all 22 series for the period 05/01/2000 – 06/02/2009.

Table 5. Conditional-co-crash probabilities for the pre-crisis period

| | Com. Wealth | Dexus | Goodman | GPT | ING Office | Macquarie office | Mirvac | Stockland | Westfield | Average of row |
|---|---|---|---|---|---|---|---|---|---|---|
| ASX-listed Property | | | | | | | | | | |
| Dexus Property Group | 18% | | | | | | | | | |
| Goodman Group | 13% | 5% | | | | | | | | |
| GPT Group | 20% | 15% | 5% | | | | | | | |
| ING Office Fund | 8% | 15% | 8% | 13% | | | | | | |
| Macquarie Office Trust | 13% | 15% | 8% | 10% | 15% | | | | | |
| Mirvac | 28% | 20% | 5% | 20% | 20% | 18% | | | | |
| Stockland | 28% | 25% | 5% | 18% | 20% | 25% | 33% | | | |
| Westfield Group | 3% | 5% | 13% | 13% | 8% | 8% | 10% | 5% | | |
| NZX-listed Property | | | | | | | | | | |
| AMP NZ Office Trust | 3% | 3% | 18% | 3% | 5% | 3% | 0% | 3% | 3% | 4% |
| Goodman Property Trust | 5% | 8% | 13% | 3% | 5% | 5% | 0% | 3% | 5% | 5% |
| Kiwi Income Property Trust | 5% | 8% | 15% | 5% | 20% | 8% | 5% | 10% | 10% | 9% |
| Property for Industry | 8% | 3% | 10% | 8% | 3% | 5% | 8% | 3% | 5% | 6% |
| Banks | | | | | | | | | | |
| AU & NZ Banking Group | 13% | 5% | 8% | 10% | 3% | 3% | 3% | 8% | 10% | 7% |
| Bank of Queensland | 5% | 10% | 15% | 5% | 3% | 5% | 8% | 3% | 8% | 7% |
| Bendigo & Adelaide Bank | 8% | 5% | 13% | 8% | 0% | 3% | 5% | 3% | 8% | 6% |
| Commonwealth Bank of AU | 5% | 10% | 15% | 13% | 5% | 3% | 3% | 5% | 15% | 8% |
| Macquarie Group | 3% | 8% | 13% | 8% | 0% | 5% | 13% | 5% | 10% | 7% |
| National Australia Bank | 8% | 8% | 13% | 10% | 3% | 8% | 3% | 3% | 8% | 7% |
| Westpac Banking | 3% | 5% | 10% | 0% | 0% | 5% | 0% | 0% | 10% | 4% |
| Indices | | | | | | | | | | |
| Bank-index | 8% | 8% | 13% | 13% | 5% | 5% | 8% | 5% | 15% | 9% |
| Property-index | 15% | 20% | 8% | 43% | 18% | 20% | 35% | 30% | 28% | 24% |

Table 5. Conditional-co-crash probabilities for the pre-crisis period

| | ANZ | Bank of Queensland | Bndigo & Adelaide | CBA | Macquarie | NAB | Westpac | Bank-index | Property-index |
|---|---|---|---|---|---|---|---|---|---|
| NZX-listed Property | | | | | | | | | |
| AMP NZ Office Trust | 0% | 0% | 3% | 3% | 0% | 3% | 0% | 3% | 0% |
| Goodman Property Trust | 5% | 8% | 5% | 10% | 3% | 5% | 5% | 10% | 5% |
| Kiwi Income Property Trust | 5% | 5% | 5% | 5% | 3% | 3% | 5% | 3% | 8% |
| Property for Industry | 8% | 3% | 8% | 8% | 10% | 8% | 5% | 10% | 8% |
| Banks | | | | | | | | | |
| AU & NZ Banking Group | | | | | | | | 43% | 13% |
| Bank of Queensland | 8% | | | | | | | 18% | 8% |
| Bendigo & Adelaide Bank | 13% | 15% | | | | | | 20% | 10% |
| Commonwealth Bank of AU | 33% | 20% | 15% | | | | | 63% | 10% |
| Macquarie Group | 13% | 18% | 13% | 30% | | | | 28% | 13% |
| National Australia Bank | 25% | 18% | 15% | 40% | 23% | | | 63% | 10% |
| Westpac Banking | 33% | 8% | 8% | 28% | 10% | 18% | | 33% | 5% |
| Indices | | | | | | | | | |
| Bank-index | 43% | 18% | 20% | 63% | 28% | 63% | 33% | | 18% |
| Property-index | 13% | 8% | 10% | 10% | 13% | 10% | 5% | 18% | |

Table 5 reports conditional-co-crash probability estimates based on equation (7) for all 22 series for the pre-crisis period 05/01/2000 – 30/04/2007.

Table 6. Conditional-co-crash probabilities for the crisis period

| | Com. Wealth | Dexus | Goodman | GPT | ING Office | Macquarie office | Mirvac | Stockland | Westfield | Average of row |
|---|---|---|---|---|---|---|---|---|---|---|
| ASX-listed Property | | | | | | | | | | |
| Dexus Property Group | 35% | | | | | | | | | |
| Goodman Group | 30% | 40% | | | | | | | | |
| GPT Group | 40% | 25% | 40% | | | | | | | |
| ING Office Fund | 55% | 35% | 25% | 15% | | | | | | |
| Macquarie Office Trust | 30% | 40% | 35% | 20% | 45% | | | | | |
| Mirvac | 40% | 50% | 20% | 35% | 40% | 25% | | | | |
| Stockland | 35% | 35% | 40% | 40% | 30% | 35% | 40% | | | |
| Westfield Group | 35% | 35% | 40% | 25% | 40% | 30% | 30% | 40% | | |
| NZX-listed Property | | | | | | | | | | |
| AMP NZ Office Trust | 25% | 25% | 15% | 15% | 25% | 20% | 30% | 20% | 15% | 21% |
| Goodman Property Trust | 15% | 30% | 15% | 15% | 10% | 10% | 20% | 15% | 10% | 16% |
| Kiwi Income Property Trust | 15% | 20% | 15% | 10% | 20% | 10% | 15% | 10% | 15% | 14% |
| Property for Industry | 0% | 10% | 15% | 5% | 10% | 15% | 10% | 5% | 5% | 8% |
| Banks | | | | | | | | | | |
| AU & NZ Banking Group | 25% | 35% | 35% | 15% | 35% | 15% | 30% | 40% | 35% | 29% |
| Bank of Queensland | 25% | 10% | 15% | 30% | 15% | 5% | 30% | 25% | 30% | 21% |
| Bendigo & Adelaide Bank | 20% | 5% | 5% | 15% | 15% | 5% | 15% | 20% | 15% | 13% |
| Commonwealth Bank of AU | 15% | 25% | 20% | 20% | 10% | 15% | 15% | 25% | 25% | 19% |
| Macquarie Group | 30% | 20% | 25% | 30% | 30% | 25% | 30% | 30% | 30% | 28% |
| National Australia Bank | 20% | 30% | 25% | 10% | 15% | 5% | 30% | 20% | 35% | 21% |
| Westpac Banking | 25% | 30% | 25% | 10% | 15% | 20% | 25% | 20% | 30% | 22% |
| Indices | | | | | | | | | | |
| Bank-index | 25% | 35% | 20% | 15% | 20% | 10% | 30% | 30% | 30% | 24% |
| Property-index | 55% | 50% | 45% | 45% | 50% | 45% | 50% | 60% | 75% | 53% |

Table 6. Conditional-co-crash probabilities for the crisis period

| | ANZ | Bank of Queensland | Bndigo & Adelaide | CBA | Macquarie | NAB | Westpac | Bank-index | Property-index |
|---|---|---|---|---|---|---|---|---|---|
| NZX-listed Property | | | | | | | | | |
| AMP NZ Office Trust | 10% | 10% | 5% | 5% | 10% | 10% | 10% | 5% | 30% |
| Goodman Property Trust | 20% | 15% | 5% | 10% | 15% | 15% | 20% | 20% | 15% |
| Kiwi Income Property Trust | 15% | 5% | 0% | 10% | 10% | 10% | 10% | 10% | 15% |
| Property for Industry | 10% | 10% | 15% | 5% | 10% | 10% | 10% | 10% | 5% |
| Banks | | | | | | | | | |
| AU & NZ Banking Group | | | | | | | | 70% | 30% |
| Bank of Queensland | 35% | | | | | | | 35% | 20% |
| Bendigo & Adelaide Bank | 30% | 40% | | | | | | 35% | 20% |
| Commonwealth Bank of AU | 45% | 15% | 20% | | | | | 60% | 25% |
| Macquarie Group | 25% | 35% | 35% | 25% | | | | 40% | 35% |
| National Australia Bank | 45% | 45% | 25% | 40% | 35% | | | 65% | 30% |
| Westpac Banking | 30% | 25% | 20% | 35% | 35% | 40% | | 45% | 30% |
| Indices | | | | | | | | | |
| Bank-index | 70% | 35% | 35% | 60% | 40% | 65% | 45% | | 30% |
| Property-index | 30% | 20% | 20% | 25% | 35% | 30% | 30% | 30% | |

Table 6 reports conditional-co-crash probability estimates based on equation (7) for all 22 series for the crisis period 01/05/2007 – 06/02/2009.

Table 7. Increased contagion risk

| Average CCC-probability | Full Sample Period | Pre-Crisis Period | Crisis Period |
|---|---|---|---|
| Bank Stocks – Bank Stocks | 36% | 19% | 32% |
| Property Stocks – Property Stocks | 38% | 14% | 35% |
| Bank Stocks – Property Stocks | 27% | 6% | 22% |
| Property Index – Bank Stocks | 34% | 10% | 27% |
| Bank Index – Property Stocks | 30% | 9% | 24% |

Table 7 reports average conditional-co-crash probability estimates for the periods the periods 05/01/2000 – 06/02/2009 (full sample period), 05/01/2000 – 30/04/2007 (pre-crisis period) and 01/05/2007 – 06/02/2009 (crisis period). The first row reports the equal-weighted mean of all CCC-probabilities between the banks only, whereas row two reports the same figure for the property firms only and row three for the banks and the property firms. Row four reports the average CCC-probability between the property index and all banks. Row five reports the average CCC-probability between the bank index and all property firms.

Table 8. Measurements of extremal linkage with the banking sector

| | Airlines | Chemicals | Consumer Goods | Food and Beverage | Healthcare | Mining | Oiland Gas | Pharmacy and Biotechnology | Property | Retail | Telecom, Media and IT | Travel and Tourism | Utilities |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CCC-probabilities full sample period | 0.28 | 0.28 | 0.22 | 0.30 | 0.30 | 0.30 | 0.32 | 0.10 | 0.36 | 0.36 | 0.22 | 0.24 | 0.28 |
| T-test difference with property sector | $1.18^{a}$ | $1.28^{a}$ | $1.92^{**}$ | $1.01^{a}$ | $1.05^{a}$ | $1.18^{a}$ | $1.04^{a}$ | $3.48^{***}$ | | 0.38 | $1.89^{**}$ | $1.59^{*}$ | $1.46^{*}$ |
| CCC-probabilities pre-crisis period | 0.10 | 0.13 | 0.18 | 0.13 | 0.23 | 0.23 | 0.23 | 0.15 | 0.18 | 0.18 | 0.15 | 0.13 | 0.08 |
| T-test difference with property sector | $1.09^{a}$ | 0.25 | 0.03 | 0.52 | 0.76 | 0.74 | 0.51 | 0.67 | | 0.35 | 0.22 | 0.57 | $1.24^{a}$ |
| CCC-probabilities crisis period only | 0.40 | 0.30 | 0.35 | 0.25 | 0.30 | 0.45 | 0.45 | 0.20 | 0.30 | 0.40 | 0.40 | 0.20 | 0.30 |

Table 8 reports conditional-co-crash probability estimates based on equation (7) between the banking sector index and 13 other sector indices for the full sample period 05/01/2000 – 06/02/2009. A T-test based on equation (3) and 600 block bootstrapped simulations is reported. It determines for each sector index whether the CCC-probability with the banking sector is statistically different from that with the property sector in the grey toned column. The superscripts $^{a}$, *, **, *** denote significance at the 15 percent, ten percent, five percent, one percent level respectively.

## Appendix I.

Figure 3. Hill-plots

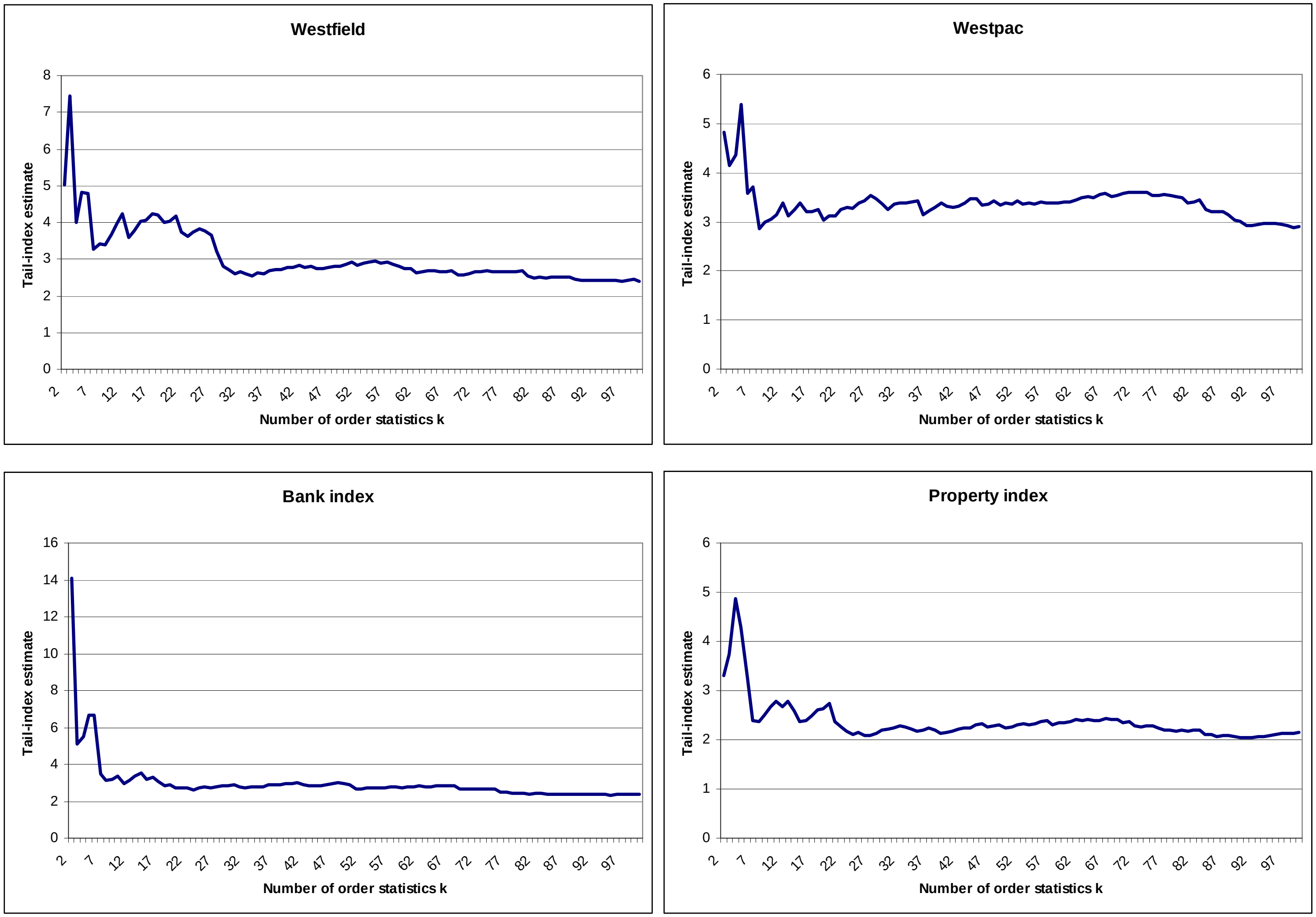


Figure 3 shows four Hill-plots which depict the relation between the number of order statistics k used in equation (2) and estimate of the tail index γ.

**Appendix II.**

Table 9. Correlation estimates for the full sample period

| | Com. wealth | Dexus | Goodman | GPT | ING Office | Macquarie office | Mirvac | Stockland | Westfield | Average of row |
|---|---|---|---|---|---|---|---|---|---|---|
| ASX-listed Property | | | | | | | | | | |
| Dexus Property Group | 0.42 | | | | | | | | | |
| Goodman Group | 0.29 | 0.28 | | | | | | | | |
| GPT Group | 0.32 | 0.41 | 0.33 | | | | | | | |
| ING Office Fund | 0.52 | 0.39 | 0.33 | 0.36 | | | | | | |
| Macquarie Office Trust | 0.38 | 0.43 | 0.25 | 0.34 | 0.44 | | | | | |
| Mirvac | 0.40 | 0.48 | 0.32 | 0.51 | 0.39 | 0.41 | | | | |
| Stockland | 0.47 | 0.50 | 0.37 | 0.50 | 0.48 | 0.43 | 0.56 | | | |
| Westfield Group | 0.39 | 0.37 | 0.30 | 0.33 | 0.38 | 0.32 | 0.34 | 0.48 | | |
| NZX-listed Property | | | | | | | | | | |
| AMP NZ Office Trust | 0.07 | 0.09 | 0.09 | 0.06 | 0.09 | 0.06 | 0.06 | 0.08 | 0.05 | 0.07 |
| Goodman Property Trust | 0.09 | 0.11 | 0.11 | 0.08 | 0.09 | 0.07 | 0.14 | 0.14 | 0.13 | 0.11 |
| Kiwi Income Property Trust | 0.08 | 0.08 | 0.03 | 0.03 | 0.11 | 0.03 | 0.09 | 0.07 | 0.07 | 0.07 |
| Property for Industry | 0.04 | 0.07 | 0.08 | 0.03 | 0.01 | 0.03 | 0.06 | 0.03 | 0.06 | 0.05 |
| Banks | | | | | | | | | | |
| AU & NZ Banking Group | 0.33 | 0.29 | 0.27 | 0.32 | 0.30 | 0.27 | 0.27 | 0.42 | 0.37 | 0.32 |
| Bank of Queensland | 0.30 | 0.26 | 0.23 | 0.25 | 0.29 | 0.24 | 0.28 | 0.33 | 0.29 | 0.27 |
| Bendigo & Adelaide Bank | 0.28 | 0.23 | 0.22 | 0.24 | 0.26 | 0.21 | 0.21 | 0.27 | 0.27 | 0.24 |
| Commonwealth Bank of AU | 0.31 | 0.27 | 0.22 | 0.25 | 0.22 | 0.21 | 0.22 | 0.34 | 0.34 | 0.26 |
| Macquarie Group | 0.32 | 0.28 | 0.27 | 0.31 | 0.31 | 0.29 | 0.24 | 0.34 | 0.33 | 0.30 |
| National Australia Bank | 0.29 | 0.24 | 0.24 | 0.31 | 0.27 | 0.26 | 0.29 | 0.39 | 0.35 | 0.29 |
| Westpac Banking | 0.28 | 0.29 | 0.22 | 0.25 | 0.22 | 0.29 | 0.25 | 0.38 | 0.32 | 0.28 |
| Indices | | | | | | | | | | |
| Bank-index | 0.35 | 0.33 | 0.28 | 0.34 | 0.3 | 0.31 | 0.3 | 0.45 | 0.41 | 0.34 |
| Property-index | 0.6 | 0.62 | 0.49 | 0.6 | 0.6 | 0.53 | 0.61 | 0.77 | 0.78 | 0.62 |

## Appendix II.

Table 9. Correlation estimates for the full sample period

| | ANZ | Bank of Queensland | Bndigo & Adelaide | CBA | Macquarie | NAB | Westpac | Bank-index | Property-index |
|---|---|---|---|---|---|---|---|---|---|
| NZX-listed Property | | | | | | | | | |
| AMP NZ Office Trust | 0.05 | 0.06 | 0.05 | 0.05 | 0.06 | 0.06 | 0.07 | 0.07 | 0.08 |
| Goodman Property Trust | 0.12 | 0.11 | 0.12 | 0.10 | 0.12 | 0.11 | 0.12 | 0.14 | 0.16 |
| Kiwi Income Property Trust | 0.05 | 0.04 | 0.05 | 0.07 | 0.04 | 0.06 | 0.04 | 0.06 | 0.09 |
| Property for Industry | 0.04 | 0.05 | 0.03 | 0.04 | 0.07 | 0.04 | 0.05 | 0.05 | 0.08 |
| Banks | | | | | | | | | |
| AU & NZ Banking Group | | | | | | | | 0.86 | 0.48 |
| Bank of Queensland | 0.42 | | | | | | | 0.49 | 0.4 |
| Bendigo & Adelaide Bank | 0.43 | 0.40 | | | | | | 0.51 | 0.36 |
| Commonwealth Bank of AU | 0.66 | 0.40 | 0.41 | | | | | 0.86 | 0.41 |
| Macquarie Group | 0.51 | 0.38 | 0.41 | 0.46 | | | | 0.58 | 0.43 |
| National Australia Bank | 0.67 | 0.42 | 0.42 | 0.65 | 0.53 | | | 0.86 | 0.45 |
| Westpac Banking | 0.72 | 0.40 | 0.40 | 0.67 | 0.45 | 0.60 | | 0.85 | 0.41 |
| Indices | | | | | | | | | |
| Bank-index | 0.86 | 0.49 | 0.51 | 0.86 | 0.58 | 0.86 | 0.85 | | |
| Property-index | 0.48 | 0.40 | 0.36 | 0.41 | 0.43 | 0.45 | 0.41 | 0.52 | |

Table 9 reports ordinary correlation estimates for all 22 return series for the sample period 05/01/2000 – 06/02/2009.

Table 10. Average correlations for the full sample period

| | Banks | Property firms |
|---|---|---|
| Banks | 0.50 | |
| Property firms | 0.28 | 0.39 |

Table 10 reports the equal weighted average correlation estimates for the full sample period 05/01/2000 – 06/02/2009 across all stocks within or between the banking and property sectors.

## Appendix III

Table 11. Summary statistics of the sector index return series

| Sector | Avg. | Min. | Max. | St.dev. | Skew | Kurt. |
|---|---|---|---|---|---|---|
| Airlines | 0.05% | -14.58% | 23.45% | 1.79% | 0.96 | 24.97 |
| Banks | 0.025% | -8.49% | 9.69% | 1.31% | 0.13 | 8.06 |
| Chemicals | 0.10% | -29.44% | 7.38% | 1.27% | 0.67 | 7.07 |
| Consumer Goods | 0.02% | -29.44% | 7.38% | 1.56% | -3.88 | 70.77 |
| Food and Beverage | 0.04% | -5.47% | 4.07% | 0.85% | -0.13 | 2.87 |
| Healthcare | 0.05% | -6.21% | 4.15% | 0.82% | -0.16 | 4.02 |
| Mining | 0.07% | -5.52% | 4.88% | 1.36% | -0.19 | 0.84 |
| Oil and Gas | 0.06% | -5.39% | 3.98% | 1.18% | -0.22 | 0.68 |
| Pharmacy and Biotechnology | 0.07% | -10.10% | 24.24% | 1.83% | 1.47 | 21.92 |
| Property | 0.000% | -11.57% | 8.03% | 1.30% | -1.25 | 14.75 |
| Retail | 0.06% | -10.30% | 6.52% | 1.05% | -1.02 | 11.65 |
| Telecom, Media and IT | 0.00% | -10.29% | 7.96% | 1.24% | -0.25 | 5.34 |
| Travel and Tourism | 0.02% | -16.43% | 21.07% | 1.81% | -0.43 | 23.51 |
| Utilities | 0.06% | -5.55% | 5.48% | 0.97% | 0.02 | 4.00 |

Table 11 reports the summary statistics of the natural logarithms of the first differences of all 14 Datastream daily total return indices over the full sample period 05/01/2000 – 06/02/2009. Columns two, three and four report the average, minimum and maximum returns. Columns five, six and seven report the standard deviation, skew and kurtosis of the return distribution.