Global financial crisis and dependence risk analysis of sector portfolios: a vine copula approach

Arreola Hernandez, Jose and Hammoudeh, Shawkat and Nguyen, Duc Khuong and Al Janabi, Mazin A. M. and Reboredo, Juan Carlos

School of Business, Humanities and Social Sciences, Instituto Tecnologico y de Estudios Superiores de Monterrey, Campus Morelia, Mexico, LeBow College of Business, Drexel University, United States Center for Energy and Sustainable Development (CESD), Montpellier Business School, Montpellier, France., IPAG Lab, IPAG Business School, Paris, France, EGADE Business School, Tecnológico de Monterrey, Santa Fe Campus, Mexico City, Mexico, Universidade de Santiago de Compostela, Spain

December 2014

Global financial crisis and dependence risk analysis of sector portfolios: a vine copula approach

Jose Arreola Hernandez[a], Shawkat Hammoudeh[b, c], Duc Khuong Nguyen[d, *], Mazin A. M. Al Janabi[e] and Juan Carlos Reboredo[f]

[a] *School of Business, Humanities and Social Sciences, Instituto Tecnologico y de Estudios Superiores de Monterrey, Campus Morelia, Mexico*

[b] *LeBow College of Business, Drexel University, United States*
[c]Center for Energy and Sustainable Development (CESD), Montpellier Business School, Montpellier, France.

[d]IPAG Lab, IPAG Business School, Paris, France

[e] *EGADE Business School, Tecnológico de Monterrey, Santa Fe Campus, Mexico City, Mexico*

[f] *Universidade de Santiago de Compostela, Spain*

Abstract

We use regular vine (*r-vine*), canonical vine (*c-vine*) and drawable vine (*d-vine*) copulas to examine the dependence risk characteristics of three 20-stock portfolios from the retail, manufacturing and gold-mining equity sectors of the Australian market in periods before, during and after the 2008-2009 global financial crisis (GFC). Our results indicate that the retail portfolio is less risky than the manufacturing counterpart in the crisis period, while the gold-mining portfolio is less risky than both the retail and manufacturing sector portfolios. Both the retail and gold stocks display a higher propensity to yield positively skewed returns in the crisis periods, contrary to the manufacturing stocks. The r-vine is found to best capture the multivariate dependence structure of the stocks in the retail and gold-mining portfolios, while the d-vine does it for the manufacturing stock portfolio. These findings could be used to develop dependence risk and investment risk-adjusted strategies for investment, rebalancing and hedging which more adequately account for the downside risk in various market conditions.

Keywords: vine copulas, risk analysis, dependence structure, retail and manufacturing stocks
JEL Classifications: C32, C51, G11

---

[*] *Corresponding author*: 184 Boulevard Saint-Germain, 75006 Paris, France. Phone: +33 (0)1 53 63 36 00 Fax: +33 (0)1 45 44 40 46.
Email addresses: J. Arreola Hernandez (jose.arreolah@itesm.mx), S. Hammoudeh (hammousm@drexel.edu), D.K. Nguyen (duc.nguyen@ipag.fr), M.A.M. Al Janabi (mazin.aljanabi@itesm.mx) and J.C. Reboredo (juancarlos.reboredo@usc.es)

1. Introduction

The important retail and manufacturing sectors of the Australian economy can be identified for having a strong relationship of dependence with the performance of the Australian grand resources sector, which includes the important gold mining sector that tends to perform well in risky market conditions, characterized by low confidence in the financial stock markets. Underlying the sectors' relationship of interdependence with the retail and manufacturing sectors, which impacts the levels of demand, spending and investment in those sectors, lies the resource-based nature of the Australian economy and the positively skewed price and return behavior of the gold market, particularly during crisis periods (Mehmedovic et al., 2011; Savills Research, 2014; Australian Retailers Association, 2014; Delloite, 2013; KordaMentha, 2013; DIISR, 2010; NAB, 2012; Green and Roos, 2012; CWT, 2012).[1]

In this context of dependence relationships, an accurate estimation and interpretation of the dependence structure and dependence risk of the stocks' of the retail, manufacturing and gold-mining sectors are of particular interest to both policymakers and investors, given these major sectors' economic linkages and dependence relationships.[2] Their dependence structure may be complex, change over time and exhibit nonlinear patterns of asymmetric behavior, thus requiring the implementation of sophisticated models that could adequately decipher the dependence dynamics at various locations of pairs of variables' joint distributions. Some of the most promising models that can be used to address the dependence structure and risk dynamics of asset portfolios are the pair vine copula models, which have been found to outperform alternative modeling techniques employed in dependence estimation (Low et al., 2013; Dismman et al., 2013; Heinen and Valdesogo, 2009).

In tune with this wave of financial risk modeling, this study employs the r-vine, c-vine and d-vine (regular, canonical and drawable, respectively) copula models to estimate and examine the dependence structure and dependence risk characteristics of three 20-stock portfolios from the Australian retail, manufacturing and gold-mining sectors in the context of the

[1] The acronyms DIISR, NAB and CWT stand for the "Department of Innovation, Industry, Science and Research", the "National Australian Bank" and the "Common Wealth Treasury", respectively.

[2] The concept of dependence risk refers to the risk stemming from a specific type of dependence relationship which two variables have in times of financial turbulence and in well-behaved financial stock markets (Hernandez, 2015). The dependence risk that two stock return series have in the center of a joint distribution is reflected as mild swings in the return distribution, as opposed to the dependence risk in the tails which is characterized by large swings in the return distribution. Besides, the dependence risk of two variables could be linear, nonlinear, symmetric or asymmetric.

GFC.[3] While the retail and manufacturing portfolios are the base of the current study, the gold-mining portfolio is included for benchmarking purposes, and due to its economic linkages and spillover effects on the retail and manufacturing sectors, particularly during crises.

Specifically, our study seeks to identify the risk profiles of the three sector portfolios and their stock market conditions under which one portfolio is riskier than another. We also examine the changes in these portfolios' conditional dependence structure across three financial period scenarios revolving around the GFC, and also identify the vine copula models that most adequately capture the multivariate dependence risk dynamics of each portfolio. For this purpose, we thoroughly analyze the size and location of the dependence concentration and its symmetric and asymmetric features for pairs of stocks' joint distributions. Moreover, a "copula counting technique" is employed to tackle the complex interpretation of the portfolios' dependence structure and their changes over different market conditions. This technique is a simple and systematic procedure to dissect, organize, analyze and interpret dependence structures in high dimensions. This specific type of methodology for multivariate dependence structure analysis draws on the dependence structure analysis approach first introduced by Arreola-Hernandez (2014). It could also be seen as an extension since it adopts a more structured and systematic approach to analyzing the multivariate dependence structure matrices. We also stress primarily the methodological aspect of the proposed approach and undertake hypothesis testing to validate or invalidate the correctness and veracity of the copula counting technique, something not conducted in Arreola-Hernandez (2014).

The vine copula models implemented in this study are based on the theory and model developments proposed by Joe (1997), Cooke (1997), Bedford and Cooke (2001, 2002) and Aas et al. (2009). While Joe (1997) discusses the construction of multivariate copulas that can be fitted to various types of dependence structures, Bedford and Cooke (2001, 2002) introduce the concept of vine copulas and develop a framework for the construction of multivariate probability distributions based on pair copulas. Aas et al. (2009) propose analytical models for the decomposition of multivariate densities and inference of the c-vine and d-vine copulas. In terms of the empirical applications and asymmetric dependence modeling, our research is broadly linked to Chollete et al. (2009)'s asymmetric dependence c-vine modeling of a portfolio consisting of stocks from the G5 and some South American countries. Heinen and Val-

[3] The acronym GFC refers to the global financial crisis that took place in the United States during the 2008-2009 period and after the collapse of the Lehman Brothers Holdings Inc, which then spread to most international financial markets. This period is characterized by a signicant degree of financial market uncertainty, volatility and risk.

desogo (2009) analyze the asymmetric dependence of 95 stocks from the S&P 500 index by employing a c-vine copula model. Dissmann (2010) uses r-vines to investigate the asymmetric dependence structure of a 16-asset portfolio consisting of equities, fixed income securities and commodity indices. Brechmann and Czado (2012) address the asymmetries and nonlinearities in the dependence structure of macroeconomic indicators by implementing a pairwise vine copula approach. More recently, Low et al. (2013) apply the Clayton c-vine copula model to asset return data. Our research is closely related to the work of Nikoloulopoulos et al. (2012), who use vine copulas to study the tail dependence of European indices. Moreover, Arreola-Hernandez (2014) recently adopts a similar framework to model the dependence structure of energy stock portfolios based on the Australian market.

The research conducted in this study, as compared to that in the above-mentioned studies, is more complete in that it thoroughly and comprehensively examines the size, location, and symmetric and asymmetric features of the dependence structure and dependence risk dynamics of three stock portfolios in the context of financial scenarios surrounding the GFC period. The financial crisis context sets the market conditions to identify dependence changes in the structure across the three financial period scenarios: the pre-GFC, GFC and post-GFC.

Our results indicate that the retail sector stock portfolio, which consists of many defensive stocks, is less dependence risky than the manufacturing portfolio in the GFC period. On the other hand, the gold-mining stock portfolio is less dependence risky than both the retail and manufacturing portfolios in similar market conditions. The lower riskiness of the retail sector portfolio relative to that of the manufacturing is due to the defensive nature of the retail stocks which include non-discretionary stocks such as those of heath care, and also since this sector has bearing to its more diversified economic linkages with most sectors of the economy, particularly its connection to the strong performance of the gold-mining sector during the crisis period. As defensive stocks, the retail stocks are recognized for having a higher propensity to yield positively skewed returns in crisis periods, a feature shared with the gold stocks but is absent in the manufacturing stocks. The r-vine and d-vine copulas are found to best capture the multivariate dependence structure of the retail, gold mining and manufacturing portfolios, respectively. Hence, our main contributions to the relevant literature come from the empirical results achieved through the implementation of the proposed “copula counting technique”.

The employed vine copula models along with the proposed copula counting technique are useful in terms of theory development and practical financial applications. Specifically, portfolio and risk managers and those who follow the trends of the Australian retail, manufacturing and gold-mining sectors may find our empirical results useful for trading and hedging purposes and for complying with capital adequacy requirements. For those end users, it is of interest to discern in more details the inherent dependence risk characteristics of these sectors, particularly in times of financial turbulence, when extreme downside events tend to occur. Those downside regimes and events are generally characterized by greater dependence across investment assets, particularly on the downside more than on the upside, and thus could severely influence the performance of the sector stock portfolios.

The remainder of this article is organized as follows. Section 2 introduces the pair vine copula models. Section 3 presents the data. Section 4 explains the bivariate copula counting technique. Section 5 deals with the empirical estimations. Section 6 concludes.

2. The pair vine copula models

The c-vine, d-vine and r-vine copula models are graph-based tree structures that make possible the design of high dimensional multivariate dependence structures. These bivariate copula-based models have become increasingly popular in the empirical domain for the analysis of multivariate real-world datasets since they allow for the estimation of random vector distributions through the assessment of copulas and marginals separately. The flexibility of these models enables one to overcome the limitations of traditional measures of dependence (e.g., bivariate copulas) and correlation (e.g., Pearson correlation), and leads to more accurate estimation of the dependence structure (Bekiros et al., 2015; Arreola-Hernandez, 2014; Aloui et al., 2011).[4]

The graphical characteristic of the pair vine copulas also enables a localized and specific-specialized modeling of marginal and joint distributional features such as kurtosis, skewness, symmetric and asymmetric dependence, through the use of bivariate copulas serving as the building blocks (Czado, 2010; Brechmann and Schepsmeier, 2011; Czado et al., 2012). The existing large set of bivariate copula families, as the building blocks of the pair vine copulas, enables one to capture various joint distributional characteristics and depend-

[4] It should be noted that the limitation of the bivariate copulas, relative to the pair vine copulas, becomes evident when the former are used in isolation (e.g., using only the Gaussian or only the Student-t bivariate copula to model a multivariate dataset). On the other hand, the strength of the pair vine copulas to a great extent stems from the simultaneous use of a wide array of bivariate copula families to model a multivariate distribution.

ence relationships between pairs of variables without altering the original marginal distributions (Low et al., 2013; Patton, 2012; Min and Czado, 2010). Both bivariate copula and pair vine copula developments have been built on the theory and mathematics proposed in the theorem of Sklar (1959).[5]

2.1 *Canonical, drawable and regular vines*

The c-vines are a subset of the r-vines that can be recognized for their star-like shape. The c-vine structure is comprised of trees, where each tree has a root node-variable selected under the criterion of having the highest correlation values with the rest of the variables. In our application, each root node is represented by a stock return series that is in a relationship of dependence with other stock return series of the dataset. Besides, in the c-vines a root node-variable (i.e., the stock return series with the strongest relationship of dependence with the rest of stock return series), which is located in the first tree, is chosen for the entire vine structure and exerts influence on the rest of the variables through high correlation values. The c-vine copulas have been acknowledged for best fitting the multivariate datasets that contain a variable that has exceptionally high correlations with the rest of the variables (Czado et al., 2013).

The d-vines, which are also a subset of the r-vines, have line tree shapes. The nodes in each tree of the d-vine cannot be linked to more than two edges. The d-vines have been found to more adequately fit multivariate datasets where a group of variables has an important influence on the rest of the variables in terms of high correlation values (Min and Czado, 2010).

The following models, along with those found in Brechmann and Schepsmeier (2011), have been proposed to separate multivariate densities and infer the pair c-vine and pair d-vine copula structures:

$$f(\boldsymbol{x}) = \prod_{k=1}^{d} f_k(x_k) \cdot \prod_{i=1}^{d-1} \prod_{j=1}^{d-i} c_{i,i+j|1:(i-1)} \left(\mathrm{F}(x_i|x_1, \dots x_{i-1}), \mathrm{F}\left(x_{i+j}|x_1, \dots, x_{i-1}\right)|\boldsymbol{\theta}_{i,i+j|\,1:(i-1)}\right) \tag{1}$$

$$f(\boldsymbol{x}) = \prod_{k=1}^{d} f_k(x_k) \cdot \prod_{i=1}^{d-1} \prod_{j=1}^{d-i} c_{j,j+i|(j+1):(j+i-1)} \left(\mathrm{F}\left(x_j|x_{j+1}, \dots x_{j+i-1}\right), \mathrm{F}\left(x_{j+i}|x_{j+1}, \dots, x_{j+i-1}\right)|\boldsymbol{\theta}_{j,j+i|\,(j+1):(j+i-1)}\right) \tag{2}$$

[5] A detailed explanation of the connection between Sklar's theorem and pair vine copula models can be found in Brechmann and Schepsmeier (2011).

where $f_k,\ k = 1, \dots, d$ denote the marginal densities and $c_{i,i+j|1:(i-1)}$ represent the bivariate copula densities with parameter (s) $\boldsymbol{\theta}_{i,i+j|\,1:(i-1)}$. Also i identifies the trees and j runs over the edges in each tree.

An r-vine on n variables is one in which two edges in tree j are joined by an edge in tree $j+1$ only if these edges share a common node. The shape of the r-vines unlike those of the c-vine and d-vines can vary significantly according to the statistical characteristics of the multivariate distribution being modeled. An exact and generalized analytical model has not been proposed for the decomposition of multivariate densities and the inference of r-vine structures, most likely because the set of possible r-vine structures is vast, diverse and complex to be captured by an equation. Despite this obstacle, Kurowicka and Cooke (2006) build the following analytical model to decompose multivariate densities and approximate the inference of the r-vine structures:

$$f(x_1, \dots, x_n) = [\prod_{k=1}^{n} f_k(x_k)] \times \left[\prod_{i=1}^{n-1} \prod_{e \in E_i} c_{j(e),k(e)|D(e)} \left(\mathrm{F}(x_{j(e)}|x_{D(e)}), \mathrm{F}(x_{k(e)}|x_{D(e)})\right)\right] \quad (3)$$

where $f(x_1, \dots, x_n)$ stands for a multivariate density, $c_{j(e),k(e)|D(e)}$ represents a bivariate conditional density copula with $j(e)$ and $k(e)$ as the conditioned nodes, and $D(e)$ as the conditioning set. The parameter $e = j(e), k(e)|\, D(e)$ is an edge that belongs to the edge set $\mathcal{E} = \{E_1, \dots, E_{n-1}\}$. The vector $\boldsymbol{X}_{D(e)}$ is a vector of variables conditioned by the components of the conditioning set $D(e)$. Eq. (3) is uniquely determined since there is not a common-based tree structure shared among the r-vine statistical models (Kurowicka and Cooke, 2006).

3. Data

We consider three 20-stock portfolios from the retail, manufacturing and gold-mining equity sectors of the Australian stock market. [6] All stocks from each sector are selected randomly. The retail and manufacturing sectors are the base of the study, while the gold-mining sector portfolio is included for benchmarking purposes, and is also due to the importance of this sector in the Australian economy. Besides, gold has the reputation of performing well in tumultuous stock market conditions, which is the focus of this study (Reboredo, 2013; Re-

[6] While the pair vine copula approach can handle portfolios of a larger size, we only consider 20-stock portfolios since the estimation of the dependence matrix becomes quite complex as the number of stocks increases. This is due to the consideration of almost all existing bivariate copula families in the modeling. The summary statistics for the constituents of these two portfolios can be made available upon request to the corresponding author.

boredo and Rivera-Castro, 2014). The manufacturing and retail stocks are selected for the analysis of dependence because their underlying market sectors are important in the Australian economy, each sector contributes roughly 5% and 6.5% of total GDP, respectively. Besides, the manufacturing sector has been in a declining trend and exhibiting increasing risk, while the retail sector has been expanding (Department of Industry, 2014; Kryger, 2014; Australian Bureau of Statistics, 2015). The backward and forward linkages the retail and manufacturing sectors have with the resources sector, the gold mining sector and other sectors of the economy also make these sectors worthy of studying (KordaMentha, 2013).

The daily stock prices are obtained from DataStream International for the period January 2005 to July 2012 and consist of 1952 observations. The study period covers three financial scenarios surrounding the 2008-2009 GFC period: the pre-GFC (January 7, 2005-July 6, 2007), the GFC (July 9, 2007-December 31, 2009) and the post-GFC (January 1, 2010-July 2, 2012). In selecting these period scenarios, we follow Baur (2012) which used similar scenarios. The Bank for International Settlements (2009) and the Federal Reserve Bank of St. Louis (2009) also use similar time periods in their analysis. The logarithmic returns are computed and then filtered with an ARMA (1,1)-GARCH (1,1) process with Student-*t* innovations to capture the leptokurtic features in the tails of the stock return distribution. The fitted parametric Student-t distribution enables one to account for extreme downturn market behaviors and economic shocks reflected in financial stock markets as large transaction volumes on the sell side and shrinkage of liquidity. The consideration of subperiods aims at capturing changes in the dependence structure of the three portfolios across time and in different market conditions. The “copula data” used to estimate the dependence structure of the three sector portfolios is obtained by applying a probability integral transform to the standardized residuals of the logarithmic returns. Table 1 displays the names of the stocks in the three portfolios and their corresponding codes.

Table 1: Names and codes of the stocks of the three portfolios

Manufacturing stock names	Manufacturing stock codes	Retail stock names	Retail stock codes	Gold stock names	Gold stock codes
Schaffer Corp.	SFCX	Coca-cola	CCLX	ST Barbara	SBMX
Boral	BLDX	Hills Hld	HILX	Northwest Resources	NWRX
Brickworks	BKWX	Gwa Grp.	GWAX	Northern Star	NSTX
Csr	CSRX	M2 Telecom	MTUX	Stone Resources of Australia	SHKX
James Hardie	JHXX	Metcash	MTSX	Degrey Mining	DEGX
Oilfield Hld.	OLHX	Woolworths	WOWX	Resolute Mining	RSGX
Colorpak	CKLX	Arb	ARPX	Apex Minerals	AXMX
Ansell	ANNX	Cash Conv.	CCVX	Orion Gold	ORNX
Sdi	SDIX	David Jones	DJSX	Redcliffe Resources	RCFX

Somnomed	SOMX	Delecta	DLCX	Excalibur Mining	EXMX
USCOM	UCMX	Harvey Norman	HVNX	Tanami Gold	TAMX
Fleetwood	FWDX	Jb Hi-Fi	JBHX	Gleneagle Gold	GLNX
Fantastic Hld.	FANX	Rcg	RCG	Millenium Minerals	MOYX
Kresta Hld.	KRSX	Specialty Fashion	SFHX	Evolution Mining	EVNX
Austal	ASBX	Super retail	SULX	Australian Mines	AUZX
Merchant House	MHIX	Wesfarmers	WESX	Hill End Gold	HEGX
Csl	CSLX	Fantastic Hld.	FANX	Kalgoorlie Mining	KMCX
Idt Australia	IDTX	Gazal	GZLX	Intermin Resources	IRCX
Codan	CDAX	Flight Centre	FLTX	Haoma Mining	HAOX
Legend	LGDX	Jetset Travel	JETX	Citigold	CTOX

4. The “copula counting technique”

The copula counting technique we propose dissects, organizes, analyzes and interprets the portfolios’ dependence structure matrix. This technique consists of the following stages: (i) counting, (ii) recording, (iii) classification, (iv) grouping and (v) aggregate dependence reading, where each stage builds on the previous one. The technique allows one to identify the most dependence risky portfolio and the stock market conditions under which that portfolio is the riskier than others. The analysis of the changes of the portfolios’ dependence structure across the three financial period scenarios is also greatly simplified through the use of this technique. Besides, by implementing the technique the vine copula models that best account for the multivariate dependence structure and risk dynamics of portfolios are easily identified.

In the literature of pair vine copula modeling, there have been some studies that have unsystematically engaged into one or two of the stages considered by the copula counting technique (e.g. Allen et al., 2013; Czado et al., 2012; Dissmann et al., 2012; Heinen and Valdesogo, 2009). Thus, the technique could be seen as an extension of those earlier attempts to organize, process, and interpret the estimates of the vine copula models’ dependence structure. For instance, Allen et al. (2013) do not count for the vine models’ bivariate copula selection. Instead, they find that the Student-*t* bivariate copula is the most frequently selected in their analysis. As a result, the information contained in the dependence structure matrix of the portfolios they consider is not fully exploited. Czado et al. (2012) do not engage into counting the bivariate copulas selected by the vine models; however, they do identify by name the selected copula families. The study by Dissmann et al. (2012), unlike those of Czado et al. (2012) and Allen et al. (2013), does engage into counting the selected bivariate copula families and records the results in tables. These authors, however, do not pursue further the classification, grouping and interpretation of the selected copulas.

The dependence risk analysis we conduct is more in-depth and is in line with the work of Heinen and Valdesogo (2009) which count, record and classify the bivariate copulas selected by the vine models. Nevertheless, those authors neither group nor aggregate the selected bivariate copulas to draw generalizations and inferences about the dependence risk features of sector portfolios. As a result, our dependence risk analysis has the comparative advantage of effectively exploiting the information contained in the portfolios' dependence structure matrices. A brief description of the techniques' stages is as follows:

i. Counting

The bivariate copulas selected by the vine models, and contained in the diagonal dependence structure matrices presented in the next section, are counted in order to know how often a certain copula is selected for the estimation of dependence between stocks. Knowing the frequency of the selection is essential because *aggregation* is used to draw generalizations and inferences about the dependence risk features of the portfolios. The aggregation of the bivariate copulas is crucial to the analysis because single bivariate copulas considered in isolation (i.e., using a single bivariate copula to model diverse pairs of variables' relationships) do not provide sufficient information about the dependence risk features of a high dimensional dependence structure.

ii. Recording

The counted bivariate copulas are organized in tables so that the patterns of the dependence and the concentration of dependence are easily recognized. The recording of the frequency of the bivariate copula selection also facilitates the identification of the dependence concentration shifts across the financial period scenarios considered or the changes in the dependence structure across time.

iii. Classification

The counted and recorded bivariate copulas selected by the vine copula models are distinguished on the basis of the type of dependence modeling they perform. This process of differentiation needs not be recorded; however, it does require from the modeler to understand the dependence modeling characteristics of each of the bivariate copulas so that they are adequately classified. An adequate classification of the bivariate copulas lays in turn a reliable ground to accurately interpret the dependence structure.

iv. Grouping

The counted, recorded and classified selected bivariate copulas are now grouped in the tables according to the type of dependence modeling they perform and the *location* of the dependence they model (i.e., center, positive tail, negative tails).

v. Aggregate dependence reading

This stage deals with the identification of the patterns of dependence, the symmetric and asymmetric features of the dependence, and the size and location of the dependence in the joint distributions. The shifts of dependence concentration between the three period scenarios and the vine copula models that best account for the overall dependence of the portfolios are recognized.

5. Empirical application

The dependence structure of the retail, manufacturing and gold portfolios is estimated by applying the c-vine, d-vine and r-vine copula models and is interpreted by using the “copula counting technique”. Table 2 lists the bivariate copula families employed by the vine copula models to measure the dependence relationships between the retail, manufacturing and gold stocks. Their corresponding conventional numbers are also listed to facilitate the estimation and interpretation of the portfolios’ dependence structure, contained in the diagonal matrices presented in this section.

Table 2: Sets of bivariate copula families employed by the vine copula models

One Param	Archimedean 2 Param	90 Rotated	180 Rotated	270 Rotated
Gaussian (1)	Clayton-Gumbel(BB1) (7)	Clayton (23)	Clayton (13)	Clayton (33)
Student-t (2)	Joe-Gumbel(BB6) (8)	Gumbel (24)	Gumbel (14)	Gumbel (34)
Clayton (3)	Joe-Clayton(BB7) (9)	Joe (26)	Joe (16)	Joe (36)
Gumbel (4)	Joe-Frank(BB8) (10)	Clayton-Gumbel(BB1) (27)	Clayton-Gumbel (BB1) (17)	Clayton-Gumbel(BB1) (37)
Frank (5)		Joe-Gumbel(BB6) (28)	Joe-Gumbel(BB6) (18)	Joe-Gumbel(BB6) (38)
Joe (6)		Joe-Clayton(BB7) (29)	Joe-Clayton(BB7) (19)	Joe-Clayton(BB7) (39)
		Joe-Frank(BB8) (30)	Joe-Frank(BB8) (20)	Joe-Frank(BB8) (40)

Notes: The bivariate copula families listed and numbered can measure linear and nonlinear dependence relationships. The Frank and the Gaussian copulas (i.e. copulas number 5 and 1 in the table) are designed to model greater dependence in the center of the joint distributions. The Clayton and the Gumbel copulas (i.e. copulas number 3 and 4 in the table) can account for the asymmetric dependence in the tails. The Student-t copula (i.e. copula number 2 in the table) models the dependence in the tails symmetrically.

The top row classifies the bivariate copulas according to the number of parameters they use and their degree of rotation. The standard elliptical bivariate copulas employ only one parameter, while the standard Archimedean bivariate copulas employ two parameters. In fact, 90, 180 and 270 degrees can rotate both the standard elliptical and the standard Archimedean bivariate copulas in order to capture distributional characteristics that the standard copulas cannot.[7]

In order to test for the portfolios' dependence risk differences or the differences in size between the portfolios' overall, asymmetric and symmetric dependence concentrations, a two-sample two-tailed t-test for the difference of means between concentrations of dependence at the 95% confidence level is conducted. The null hypothesis H_o tested is: "*No statistically significant difference exists between the means of two concentrations of dependence.*" The t-test to be fitted is:

$$t = \frac{The\ difference\ between\ sample\ means}{Estimated\ standard\ error\ of\ difference\ between\ means}$$

$$t = \frac{\bar{x}_1 - \bar{x}_2}{S_{\bar{x}_1 - \bar{x}_2}}, \tag{4}$$

where $S_{\bar{x}_1 - \bar{x}_2} = \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}$ (5)

In Eq. (5), the variables s_1^2 and s_2^2 represent the sample variances, and n_1 and n_2 account for the numbers of observations in the respective samples. The degrees of freedom are estimated as follows:

$$df = (n_1 - 1) + (n_2 - 1) \tag{6}$$

If the null hypothesis is rejected, then the concentration of dependence accounted by n_1 is identified as being s*ignificantly larger, significantly smaller or neither* (somewhere in the middle). The null hypothesis is rejected if the T-test value t is greater than the t statistic. In other words, the null hypothesis is rejected if $t > t_{(0.05,22)=} \pm 2.074$ at the 95% confidence level and 22 degrees of freedom.

5.1. The retail portfolio

Figure 1 displays the r-vine diagonal dependence structure and the Kendall tau matrices of the retail portfolio. All matrices consist of 192 components. The numbers in the diagonal dependence structure matrices of Panel (a) represent the bivariate copulas listed and numbered in Table 2.

---

[7] Since the dependence structure corresponding to each financial period scenario is recorded in tables as part of the recording stage, the counting stage of the technique is only implemented to the full sample period scenario of each portfolio. The output from the counting, recording and classification stages is summarized in the grouping stage. Also, only the Kendall tau and the dependence structure matrices of the retail and manufacturing portfolios for the one period scenario are shown.

According to Figure 1 and Table 3 of the retail portfolio, the bivariate copulas that are more frequently selected by the c-vine, d-vine and r-vine copulas, under the full sample period scenario, to measure the dependence in the pairs of stocks' joint distributions are: the Frank (5) selected 38, 44 and 51 times for the c-vine, the d-vine and the r-vine models, respectively; the Joe-Frank 180 degrees rotated (20) 9, 6 and 8 times; the Joe-Frank (10) 7, 5 and 3 times; the Gaussian (1) 18, 16 and 18 times; the Clayton (3) 11, 9 and 7 times; the Student-t (2) 45, 43 and 41 times; the Gumbel 180 degrees rotated (14) 14, 13 and 12 times; the Clayton 180 degrees rotated (13) 18, 15 and 16 times each; the Joe 180 degrees rotated (16) 5, 3 and 3 times; and the Gumbel (4) 10, 7 and 8 times.

5																		
5	5																	
33	1	3																
16	3	30	1															
36	4	2	14	1														
26	33	5	14	1	1													
5	10	3	3	1	23	13												
13	26	10	13	13	1	1	5											
13	5	2	5	20	24	14	2	13										
3	20	4	1	5	3	5	36	14	5									
5	26	5	5	5	34	1	5	33	13	30								
5	2	5	5	1	10	5	5	2	36	10	30							
1	20	5	1	1	3	2	16	5	2	4	2	4						
23	33	5	4	34	5	33	5	1	14	10	5	1	30					
1	1	5	1	24	1	13	5	13	4	10	20	2	5	5				
14	5	5	10	10	5	33	5	13	36	5	5	3	5	5	5			
1	13	2	1	3	5	1	2	4	5	5	20	2	2	2	9	2		
2	1	5	6	4	14	1	5	5	3	5	5	33	5	5	5	5	5	
13	7	2	13	20	5	2	1	20	19	14	5	20	1	5	1	1	1	3

5																		
6	40																	
26	13	24																
5	33	1	40															
1	5	1	5	1														
14	5	16	13	24	24													
4	20	13	5	2	5	36												
5	5	1	5	5	33	3	5											
4	23	5	5	5	2	13	20	36										
5	23	1	5	5	5	5	24	5	1									
1	23	3	4	20	20	5	5	40	5	5								
5	10	23	13	13	5	5	5	5	3	26	13							
13	4	5	13	23	13	2	5	13	2	16	2	1						
13	5	5	10	5	1	5	2	23	1	5	3	3	13					
5	5	4	20	20	33	3	3	23	3	1	2	5	14	5				
10	5	4	10	1	5	1	5	14	5	5	5	1	36	2	10			
2	1	5	5	5	1	2	20	1	14	2	2	20	3	36	20	5		
1	2	13	2	2	1	14	5	5	5	20	5	2	20	3	2	2	5	
2	10	10	14	1	5	2	5	3	3	19	20	7	2	14	1	1	5	5

Panel (a)

-0.03																		
0.02	-0.063																	
-0.014	0.016	-0.006																
0.057	-0.005	0.006	-0.041															
-0.005	0.059	0.009	0.025	0.019														
0.01	0.063	0.001	0.019	-0.02	-0.002													
0.042	0.103	0.006	0.084	0.022	-0.011	-0.003												
0.063	0.157	-0.011	0.082	0.08	-0.001	0.007	0.027											
0.017	-0.013	0.047	0.105	0.079	0.015	0.026	0.053	-0.001										
0.056	-0.016	0.014	0.192	0.145	0.11	0.082	-0.013	-0.057	0.005									
0.021	-0.006	0.01	0.015	0.2	0.213	0.063	0.1	-0.115	0.037	-0.01								
0.024	0.069	-0.002	0.026	0.023	0.302	0.146	0.047	-0.251	0.019	-0.015	0.002							
0.028	0.016	0.067	0.015	-0.013	0.002	0.282	0.164	0.011	0.038	0.019	0.018	0.003						
0.009	0.133	0.031	0.063	-0.007	0.002	-0.02	0.336	-0.006	0.043	0.021	0.023	0.014	0.002					
0.183	0.232	0.005	0.024	0.093	-0.001	0.011	0.032	-0.006	0.028	0.103	0.072	-0.018	0.017	-0.011				
0.209	0.286	0.001	0.163	0.025	0.128	0.021	0.04	0.002	0.02	0.053	0.063	0.065	-0.011	0.015	0.213			
0.359	0.059	-0.016	0.155	0.259	0.011	0.096	0.069	-0.003	0.06	0.059	0.043	0.062	0.02	-0.013	0.252	0.361		
-0.003	0.21	0.005	0.149	0.296	0.002	0.078	0.114	0.056	0.064	0.081	0.104	0.098	0.088	0.042	0.649	0.665	-0.021	
0.644	0.108	0.114	0.049	0.091	0.429	0.097	0.14	0.014	0.096	0.16	0.176	0.254	0.308	0.164	0.086	0.125	0.099	0.539

Panel (b)

Fig. 1: The dependence structure and Kendall tau matrices of the retail portfolio. Panel (a) displays the full sample period's r-vine (on the left) and c-vine (on the right) copula family specification matrices. Panel (b) displays the full sample period's r-vine Kendall tau correlation matrix.

Table 3 summarizes the counting, recording, classification and grouping stages of the copula counting technique. The Frank copula is selected the most by the vine copula models, implying that most of the dependence in the retail portfolio is concentrated in the center of the joint distributions for the pairs of stocks. As indicated, due to the predominance of the Frank copula under all financial period scenarios for the retail portfolio, most of the dependence is concentrated in the center of this portfolio's joint distribution, implying that the retail stocks have a high dependence risk in the non-crisis periods and low dependence risk in the financial crisis periods. This finding in turn implies that the returns of the retail portfolio are liable to change more frequently in the non-crisis periods but have a low probability of being extreme in those market conditions, due to the moderate movements in the fundamental macroeconomic variables during that period. Looking back into the 2008-2009 global financial crisis indicates that stock investments in the Australian retail sector were indeed exposed to lower market risk in comparison with similar investments in the United States' retail sector and the Australian manufacturing sector. The primary reason for the lower risk exposure of the Australian retail sector during the crisis period, as compared to the US retail sector, is that the Australian economy has a strong resource-based economic component, and unlike that of the United States' retail sector, has a tight economic relationship of dependence with the performance of the gold mining sector and other non-resources sectors of the Australian economy. In the U.S., the retail sector is tied more to the volatile consumer confidence that is in turn influenced by the job market as a whole.

Table 3: The c-vine, d-vine and r-vine models' bivariate copula selection for the retail portfolio

Bivariate Copula	**Full sample**			**Pre-GFC**			**GFC**			**Post-GFC**		
Vine model	C vine	D vine	R vine	C vine	D vine	R vine	C vine	D vine	R vine	C vine	D vine	R vine
							Negative tail					
Clayton	11	9	7	18	17	18	25	21	20	13	15	16
Gumbel 180	14	13	12	12	8	9	13	10	10	13	11	9
Studen-t	45	43	41	17	15	16	23	25	31	20	18	21
Joe 180	5	3	3	2	3	5	3	4	6	4	3	5
Joe-Frank 180	9	6	8	9	7	10	4	3	4	4	2	3
Clayton 270	2	4	7	9	8	10	6	4	5	3	3	5
							Center					
Frank	38	44	51	52	53	58	46	44	49	47	43	45
Gaussian	18	16	18	28	24	22	21	19	21	31	27	25
							Positive tail					
Gumbel	10	7	8	5	7	10	9	7	6	10	9	12
Clayton 180	18	15	16	9	7	10	15	13	15	20	19	21
Clayton 90	4	5	6	10	8	10	7	5	3	7	5	4
Studen-t	45	43	41	17	14	16	23	25	31	20	19	21
Joe	4	3	4	7	5	2	5	6	8	7	6	9
Joe-Frank	7	5	3	6	5	4	4	3	1	2	1	3

Notes: The full sample period spans from January 2005 to July 2012; the pre-GFC stretches from Jan 2005 to July 2007; the GFC period covers from July 2007 to Dec 2009 and; the post-GFC period accounts for the volatility between Jan 2010 and July 2012. The numbers in the table represent the number of times a bivariate copula function is selected. The Student-t copula is positioned with copulas for both positive and negative tail dependence because it measures the dependence in both tails symmetrically. This symmetric aspect of the Student-t copula poses a challenge to the interpretation of the dependence structure because it is unclear in which tail of the distribution the dependence is concentrated.

In essence, the retail sector had gone through moderate economic shocks during the financial crisis, mainly because the Australian gold-mining sector and other resources and non-resources sectors had overall outmaneuvered the financial crisis' effects fairly well. Evidence of this is that the gold-mining sector had its best historical performance during the crisis period, with gold prices escalating sharply. Coal, uranium and gas prices did fall in the short term, as a consequence of the financial turmoil. However, the increased demand for commodities (stemming from their price declines) offsets the losses partially (Arreola et al., 2014). The relative stability the uranium prices enjoyed during the crisis period is identified to have to do with the underlying price drivers, which appear not to be directly linked to the traditional macroeconomic fundamentals.[8] The early intervention of the Australian government to stimulate the economy through fiscal and monetary policies had also, but to a lesser degree, impacted the consumption and investment in the retail sector.

The most significant shift of dependence concentration in the retail portfolio is observed to take place from the pre-GFC to the GFC periods. Specifically, the dependence structure is observed to move from the center of the joint distribution towards the end of the tails. This shift of dependence concentration reflects the highly volatile conditions in the financial stock markets during the GFC and the high propensity of some discretionary retail stocks in the portfolio (those with greater concentration of asymmetric dependence in the negative tail) to yield negatively skewed returns in those market conditions.

The copulas for modeling the positive tail dependence have their largest presence in the post-GFC period, indicating a recovery in the financial stock markets and a high probability of the retail stocks to realize positively skewed returns in those market conditions. However, the shift of dependence concentration shows that the retail sector recovered at a slow pace in the post-crisis period. Alternative research in the field also indicates that the retail sector recovered at a slow pace in the post-crisis period. Its recovery is linked to the revival of the iron ore prices, the increase in financial stock market confidence and the depreciation of the Australian dollar (Delloite, 2011; AGPC, 2011).[9]

---

[8] The strong relationship of dependence the Australian economy has with the mining and energy sectors is a common feature shared by the Canadian economy.

[9] It should be noted that the iron ore commodity plays a key role in the Australian resources economy. For instance, in 2011 Australia occupied the first place in exports of iron ore worldwide, producing 40 per cent of the global iron ore exports. During the global financial crisis (in the period Oct-2008 to Dec-2009) iron ore prices

In order to identify the vine copula model that best accounts for the multivariate dependence structure of the retail portfolio, through the use of the copula counting technique, we look at the frequency of the selection of the Frank copula across the period scenarios. This is because most of the dependence in the portfolio is located in the center of the joint distributions, as indicated above. The vine model's frequency of the selection of the Frank copula under the full sample period scenario is given more weight since that period scenario accounts for the changes of the dependence structure between the pre-GFC, GFC and post-GFC period scenarios. In the full sample period, the pre-GFC and the GFC period scenarios, the r-vine model clearly selects the Frank copula the most, relative to the c-vine and d-vine. In the post-GFC the c-vine selects it more frequently. Hence, according to the copula counting technique, the r-vine is the model that most accurately approximates the multivariate dependence structure of the retail portfolio. In Subsection 5.5, we undertake a goodness of fit testing on the vine models fitted to validate or invalidate the copula counting technique findings.

The relative comparison of the dependence concentration of the portfolios modeled in our paper shows that the retail portfolio's dependence concentration in the center is at the 95% confidence level, significantly larger than that of the manufacturing. This concentration is also significantly smaller than that of the gold-mining portfolio (refer to Subsection 5.3 where we undertake the significance testing of dependence concentration comparisons). This information implies that the retail portfolio is less dependence risky than the manufacturing portfolio during times of financial turbulence. But it is more dependence risky than the gold portfolio in similar market conditions. These findings are confirmed by the empirical results on the manufacturing and gold portfolios presented in Subsections 5.2 and 5.3. The findings also appear to be consistent with the performance of the retail, manufacturing and gold-mining sectors during the crisis period. The retail sector, in general, had a better performance than the manufacturing sector during the crisis period (KordaMentha, 2013; NAB, 2012; Green and Roos, 2012; CWT, 2012; Baur and McDermott, 2010; Baur and Lucey, 2010; DIISR, 2010). A possible explanation for this behavior is that a greater percentage of the money yielded by the gold-mining sector's performance and in circulation was spent and invested for the acquisition of basic household and livelihood goods, rather than for durables that require larger investment and capital.

---

suffered a sharp decline, losing 48 per cent in their value (from US$138 per tonne to US$71 per tonne) (Bingham and Perkins, 2012).

Given the specific risk characteristics of the retail portfolio during the crisis periods, investments in its underlying sector could be used to hedge investment positions in alternative sectors that have high dependence risk during crisis periods, or be used as part of a risk management framework for downside risk. In relation to the sector portfolios modeled in our paper, investments in the retail sector could be used to hedge an investment position in the manufacturing sector during crisis periods and an investment position in the gold sector as the financial stock markets transit from crisis to non-crisis.

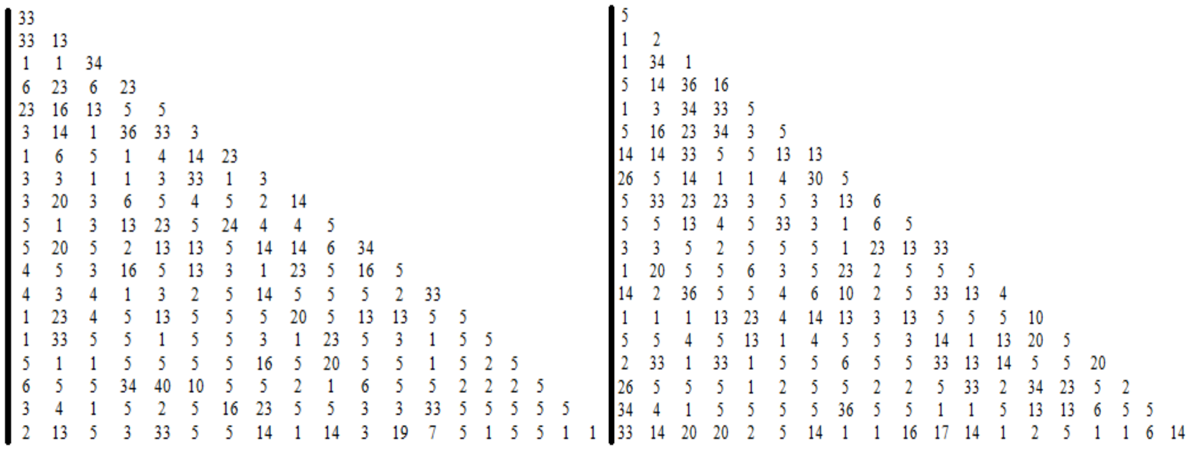
5.2. The manufacturing portfolio

Figure 2 displays the r-vine diagonal dependence structure and the Kendall tau matrices of the manufacturing portfolio. Table 4 reports the vine models' bivariate copula selections. The results show that most of the dependence for the manufacturing sector is also concentrated in the center, with the Frank copula being the most frequently selected by the vine copula models under each of the four financial period scenarios. While having most of the dependence concentrated in the center, the manufacturing portfolio has a smaller concentration of dependence than the retail. As a consequence, it is more dependence risky than the retail during the crisis periods. This dependence risk difference makes the return values of the manufacturing portfolio liable to change less frequently than those of the retail in non-crisis periods, and have a higher probability of being extreme in crisis periods. As a consequence, the manufacturing portfolio is riskier than the retail portfolio because greater losses can be incurred during the crisis periods.

5																		
5	5																	
33	1	3																
16	3	30	1															
36	4	2	14	1														
26	33	5	14	1	1													
5	10	3	3	1	23	13												
13	26	10	13	13	1	1	5											
13	5	2	5	20	24	14	2	13										
3	20	4	1	5	3	5	36	14	5									
5	26	5	5	5	34	1	5	33	13	30								
5	2	5	5	1	10	5	5	2	36	10	30							
1	20	5	1	1	3	2	16	5	2	4	2	4						
23	33	5	4	34	5	33	5	1	14	10	5	1	30					
1	1	5	1	24	1	13	5	13	4	10	20	2	5	5				
14	5	5	10	10	5	33	5	13	36	5	5	3	5	5	5			
1	13	2	1	3	5	1	2	4	5	5	20	2	2	2	9	2		
2	1	5	6	4	14	1	5	5	3	5	5	33	5	5	5	5	5	
13	7	2	13	20	5	2	1	20	19	14	5	20	1	5	1	1	1	3

5																		
13	13																	
13	16	3																
13	2	23	3															
3	3	2	3	5														
36	23	2	3	23	40													
1	5	2	3	1	5	5												
5	33	5	2	1	1	5	3											
5	3	14	36	5	36	5	1	16										
5	14	1	5	14	26	16	14	5	24									
33	4	16	6	1	3	40	4	16	3	5								
5	10	16	5	5	3	1	2	3	26	23	5							
13	14	24	2	14	2	20	2	5	4	2	16	14						
1	3	4	3	5	6	1	40	5	6	10	5	6	13					
2	2	3	3	5	5	13	5	20	14	14	3	1	3	16				
13	5	4	26	1	5	1	2	1	13	1	5	5	5	33	2			
33	1	13	34	1	6	10	16	6	16	2	2	33	5	5	2	3		
5	5	5	1	1	5	2	5	1	1	10	5	16	5	33	5	5	5	
19	16	3	16	6	13	3	5	7	14	14	13	16	5	3	3	1	13	16

Panel (a)



Panel (b)

Fig. 2: The dependence structure and the Kendall tau matrices of the manufacturing portfolio. Panel (a) displays the full sample period's r-vine (on the left) and c-vine (on the right) dependence structure matrices of the manufacturing portfolio. Panel (b) displays the GFC period's r-vine (on the left) and c-vine (on the right) dependence structure matrices of the manufacturing portfolio. All matrices consist of 192 components. The numbers in the diagonal dependence structure matrices represent the bivariate copulas listed and numbered in Table 2.

A look into the Australian economy from economic and financial perspectives suggests that the higher riskiness of the manufacturing portfolio stems from the pro-cyclicality of some products of the manufacturing sector and the interdependence and multiplier effects it has with the overall resources sector, which is an important driver of the Australian economy. Specifically, the economic linkages the overall resources sector and the gold-mining sector have with the Australian manufacturing sector are different from those economic linkages those sectors have with the Australian retail sector. The economic linkages with the manufacturing sector are more volatile, have a higher degree of uncertainty and deal with higher levels of risk aversion since spending and investment in the manufacturing sector tends to require more capital (Pilat et al. 2006). Hence, the Australian manufacturing sector overall has a higher exposure to risk than the Australian retail sector does.

Table 4: The c vine, d-vine and r-vine models' bivariate copula selections for the manufacturing portfolio

Bivariate Copula	**Full sample**			**Pre-GFC**			**GFC**			**Post-GFC**		
Vine model	C vine	D vine	R Vine	C vine	D vine	R vine	C vine	D vine	R vine	C vine	D vine	R vine
						Negative Tail						
Clayton	11	9	12	24	15	14	20	14	14	10	9	11
Gumbel 180	8	8	7	11	15	8	8	13	5	12	12	11
Studen-t	17	24	21	18	23	28	11	15	12	13	17	19
Joe 180	2	1	2	15	11	14	5	7	9	3	4	6
Joe-Frank 180	8	9	12	2	0	4	4	4	5	5	3	2
Clayton 270	7	5	3	6	7	7	8	6	9	11	9	5
						Center						
Frank	56	68	60	45	42	48	65	66	69	61	59	57
Gaussian	30	15	23	22	24	23	25	23	21	25	27	32
						Positive Tail						

Gumbel	8	6	6	5	5	3	9	11	10	8	6	2
Clayton 180	13	9	14	13	14	10	10	10	11	14	17	19
Clayton 90	2	6	7	4	12	11	0	8	3	7	6	5
Studen-t	17	24	21	18	23	28	11	15	12	13	15	19
Joe	1	3	1	7	3	3	7	3	3	7	5	5
Joe-Frank	8	12	7	4	1	3	1	2	7	2	3	2

Notes: The full sample period spans from January 2005 to July 2012; the pre-GFC stretches from Jan 2005 to July 2007; the GFC period covers from July 2007 to Dec 2009 and; the post-GFC period accounts for the volatility between Jan 2010 and July 2012. The numbers in the table represent the number of times a bivariate copula function is selected. The Student-t copula is positioned with copulas for both the positive and negative tail dependence because it measures dependence in both tails symmetrically. This symmetric aspect of the Student-t copula poses a challenge to the interpretation of the dependence structure because it is unclear in which tail of the distribution the dependence is concentrated.

Besides, due to the predominance of the Frank copula in the GFC period scenario, the returns of the manufacturing portfolio appear to be driven by complex relationships of dependence in the center. On the other hand, the reduced presence of the Frank copula and the increased presence of the Gaussian during the post-GFC indicate that the dependence relationships of the manufacturing stocks during the post-crisis period are more of the linear type. The increased presence of the Gaussian copula may also be an indication of the reduced volatility in the post-crisis period, and of a less chaotic world of dependence relationships.

Unlike in the retail portfolio, the Student-t copula in the manufacturing portfolio has its smallest presence in the GFC and its largest presence in the pre-GFC, confirming that the manufacturing stocks are riskier than the retail stocks in crisis periods and have a high propensity of yielding negatively skewed returns in those market conditions. From the GFC to the post-GFC periods, the dependence structure is observed to shift only slightly, with minor increases in the number of stocks having positive tail dependence. This observation suggests that the Australian manufacturing sector lagged behind the effects of the financial crisis until the end of 2012, and as a consequence, recovered at a slower pace than the retail sector. The Australian Department of Innovation, Industry, Science and Research confirms that the manufacturing sector recovered at a slower pace during the post-crisis period relative to the retail sector (KordaMentha, 2013; DIISR, 2010; NAB, 2012, Green and Roos, 2012; CWT, 2012).[10]

The significance testing of dependence concentration displayed in Subsection 5.4 confirms that the manufacturing portfolio has a smaller concentration of dependence in the center of the joint distributions relative to the retail portfolio, making it more dependence risky during crisis periods. Also, while the manufacturing portfolio has a higher propensity to yield negatively skewed returns, the retail portfolio tends to yield positively skewed ones. With

[10] The acronyms DIISR, NAB and CWT stand for: the Department of Innovation, Industry, Science and Research; the National Australian Bank; and the Common Wealth Treasury, respectively.

respect to model selection, the d-vine overall is recognized to select the Frank copula most frequently to model dependence of the manufacturing stocks. Specifically, by means of the copula counting technique it is observed that under the full sample period scenario, the d-vine selects the Frank copula the most, relative to the c-vine and r-vine. Despite the r-vine selecting the Frank copula the most under the pre-GFC and the GFC period scenarios and the c-vine doing it in the post-GFC, the priority given to the full sample period scenario leads to the identification of the d-vine as the most adequate model.

Considering the specific risk characteristics of the Australian manufacturing stock portfolio, investments in the underlying sector are to be avoided during crisis periods and be taken with caution in normal market conditions. As part of a hedging strategy or a risk management framework, investments in the manufacturing sector could serve best against investment positions with higher risk in non-crisis periods or in normal market conditions.

5.3. The gold portfolio

According to Table 5, most of the dependence in the gold-mining portfolio is concentrated in the center of the joint distributions, indicating that this equity sector has low dependence risk in times of financial turbulence and high dependence risk when the financial stock markets behave smoothly. This specific type of dependence risk feature is found to be coherent with the price behavior of gold during the 2008-2009 global financial crisis. Gold-mining stocks during the GFC and part of the post-GFC periods displayed an exceptionally strong negative correlation with the financial stock market confidence. They reached historical levels and were perceived by investors as a “relatively secure defensive investment and storage of wealth” (Collins, 2013). The high concentration of dependence the gold-mining stock portfolio has in the center also implies that its return values are liable to change more frequently when the stock markets are tranquil and less frequently when the stock markets lack the investors’ confidence. Gold-mining stocks could therefore be used to hedge an investment position in the manufacturing sector primarily but also in the retail sector during the crisis periods.

Table 5: The c-vine, d-vine and r-vine models’ bivariate copula selection for the gold portfolio

Bivariate Copula	**Full sample**			**Pre-GFC**			**GFC**			**Post-GFC**		
Vine model	C Vine	D Vine	R vine	C vine	D Vine	R vine	C vine	D vine	R vine	C Vine	D vine	R vine
						Negative Tail						
Clayton	6	8	11	12	18	19	9	11	12	15	12	18
Gumbel180	16	16	15	22	14	14	14	15	12	9	12	11
Studen-t	20	23	21	14	14	17	16	19	21	19	17	19
Joe 180	1	8	8	15	15	10	3	7	6	0	0	8
Joe-Frank 180	26	28	19	0	0	8	8	8	11	0	0	6

Clayton 270	0	0	0	5	8	0	0	0	0	5	7	0
Centre												
Frank	54	46	54	48	49	51	85	69	72	58	59	53
Gaussian	17	17	15	27	25	22	17	21	18	30	26	28
Positive Tail												
Gumbel	15	14	11	13	4	10	0	0	3	9	11	9
Clayton 180	0	0	6	11	18	14	8	6	13	10	11	9
Clayton 90	4	5	0	4	4	0	0	0	0	7	8	0
Studen-t	20	23	21	14	14	17	16	19	21	19	17	19
Joe	0	0	3	0	0	3	0	0	5	0	0	6
Joe-Frank	15	16	20	7	3	2	7	8	4	0	0	4

Notes: The full sample period spans from January 2005 to July 2012; the pre-GFC stretches from Jan 2005 to July 2007; the GFC period covers from July 2007 to Dec 2009 and; the post-GFC period accounts for the volatility between Jan 2010 and July 2012. The numbers in the table represent the number of times a bivariate copula function is selected. The Student-t copula is positioned with copulas for both positive and negative tail dependence because it measures the dependence in both tails symmetrically. This symmetric aspect of the Student-t copula poses a challenge to the interpretation of the dependence structure because it is unclear in which tail of the distribution the dependence is concentrated.

The noticeable decrease of the copulas for the modeling of asymmetric dependence in the negative tail from the pre-GFC to the GFC period scenarios confirms the immunity of gold to financial crisis periods' effects. As to model selection, the r-vine copula model overall is observed to most frequently select the Frank copula under most of the considered period scenarios. Thus, it is discerned to be the model that best captures the multivariate dependence structure and dependence risk dynamics of the gold-mining stock portfolio. The significance testing of dependence concentration confirms that the gold portfolio is less dependence risky than the retail and manufacturing during crisis periods. As a consequence, investments in its underlying sector are desirable during crisis periods, preferable to investments in the retail and manufacturing sectors in similar market conditions, while being used in hedging strategies and risk management frameworks to deal with downside risk.

5.4. Significance testing of dependence concentration comparison

The results of the dependence concentration comparison are based on the two-tailed t-test fitted to account for the difference in means between the portfolios' concentrations of dependence. As indicated above, we have tested the null hypothesis H_o: "*No statistically significant difference exists between the means of two concentrations of dependence.*" The null hypothesis is rejected if $t > t_{(0.05,22)} = \pm 2.074$. Table 6 displays the t-test values for the difference of the means of the portfolios' relative comparison of overall, asymmetric and symmetric dependence concentration. The asymmetric dependence comparison looks at the dependence concentration in the negative and positive tails for the Clayton and the 180 degree-rotated Gumbel, Joe, and Joe-Frank copulas. The comparison of symmetric dependence in both tails looks at the dependence concentration for the Student-t copula, while the dependence concentration in the center is compared for the Frank copula. According to the relative comparison of dependence concentration displayed in Table 6, the retail portfolio's overall dependence concentration (e.g., in the center) is significantly larger than that of the manufacturing portfolio at the 95% confidence level. In addition, the dependence concentration of gold portfolio in the center is at the same confidence level significantly larger than that of the retail portfolio. As a result, the gold portfolio has also a significantly larger concentration of dependence than the manufacturing portfolio in the center.

Table 6: Test for the differences of means between the sectors portfolios' dependence concentration**.**

Significance testing of dependence	**Gold vs. Retail**	**Retail vs. Manufacturing**
Overall dependence (center)		
Frank T-test	3.02*	3.34*
Statistical significance	Sig. larger	Sig. larger
Overall dependence (negative tail)		
Clayton T-test	-0.84	0.75
Gumbel 180 T-test	2.87*	1.38
Joe 180 T-test	2.00	-2.46*
Joe-Frank 180 T-test	1.35	-0.35
Statistical significance	Neither	Neither
Overall dependence (positive tail)		
Gumbel T-test	-0.05	1.95
Clayton 180 T-test	-3.14*	1.35
Joe T-test	-4.85*	1.81
Joe-Frank T-test	1.86	-0.45
Statistical significance	Sig. smaller	Neither
Symmetric dependence (tails)		
Student-t T-test	-2.56*	2.44*
Statistical significance	Sig. smaller	Sig. larger
Asymmetric dependence (negative tail)		
Clayton T-test	-0.84	0.75
Gumbel 180 T-test	2.87*	1.38
Statistical significance	Sig. larger	Neither
Asymmetric dependence (positive tail)		
Gumbel T-test	-0.05	1.95
Clayton 180 T-test	-3.14*	1.35
Statistical significance	Sig. smaller	Neither
Critical value= $t_{(0.05,22)}$=± 2.07		

Notes: The table displays the t-test values for the difference of means between the portfolios' concentration of dependence in the center, the negative tail and the positive tail. The null hypothesis of equality is rejected if $t > t_{(0.05,22)=} \pm 2.074$, and marked by an asterisk (*). When four copulas are used to determine the statistical significance, we require that the t-values of at least two copulas are larger or smaller than the critical value. When only two copulas are used to determine the statistical significance, we require that the t-value of at least one copula is larger or smaller than the critical value.

5.5 Vine copula models' goodness-of-fit testing

In Subsections 5.1, 5.2 and 5.3 it was found through the use of the copula counting technique, that the r-vine and the d-vine respectively are the models that most accurately approximate the multivariate dependence structure of the retail, manufacturing and gold-mining portfolios. This section implements the *ECP* and *ECP2* goodness-of-fit tests, which are based on the empirical copula processes to validate or invalidate those findings. The tests are non-parametric and are based on the Cramer-von Mises (*CvM*) and Kolmogorov-Smirnov (*KS*) test statistics, which use a 95% confidence level. Our motivation for the specific selection of these tests is that, relative to the Akaike and Bayesian Information Criteria, they are more reliable sources of information regarding the goodness-of-fit of the pair vine copula models fitted (Schepsmeier, 2013; Genest et al., 2009; Panchenko, 2005). The objective is therefore to identify the pair vine copula model that most closely approximates the multivariate dependence structure of the gold, retail and manufacturing portfolios.

The following alternative hypothesis is tested:

H_a : *There is a pair vine copula model that best captures the dependence structure of the portfolios.*

The specified confidence level in the CvM and *KS* test statistics employed by the *ECP* and *ECP2* is 95%. In practice, the *ECP* and *ECP2* measure the distance between the fitted parametric marginal and joint distributions and the empirical marginal and joint distributions of the observations.

Table 7: Gold, retail and manufacturing portfolios' goodness-of-fit testing for the c-vine, d-vine and r-vine

Portfolios and copulas	**Gold**			**Retail**			**Manufacturing**		
	c-vine	d-vine	r-vine	c-vine	d-vine	r-vine	c-vine	d-vine	r-vine
Full sample									
ECP(*CvM*)	*ts*=0.016 *p*=0.44	*ts*=0.003 *p*=0.975	*ts*=0.004 *p*=0.98	*ts*=0.011 *p* =0.65	*ts*=0.0093 *p* =0.87	*ts*=0.00 *p*=0.96	*ts*=0.023 *p*=0.19	*ts*=0.0033 *p* =0.98	*ts*=0.021 *p*=0.67
ECP2(*CvM*)	*ts*=0.000 *p*=1.00	*ts*=0.000 *p*=1.00	*ts*=0.000 *p*=1.00	*ts*=0.000 *p*=1.00	*ts*=0.000 *p* =1.00	*ts*=0.000 *p*=1.00	*ts*=0.000 *p*=1.00	*ts*=0.000 *p* =1.00	*ts*=0.000 *p*=1.00
ECP (*KS*)	*ts*=1.825 *p*=0.23	*ts*=0.952 *p*=0.425	*ts*=1.339 *p*=0.04	*ts*=1.200 *p*=0.505	*ts*=1.597 *p* =0.14	*ts*=1.275 *p*=0.61	*ts*=1.498 *p*=0.38	*ts*=1.089 *p* =0.21	*ts*=2.293 *p*=0.15
ECP2(*KS*)	*ts*=0.022 *p*=1.00	*ts*=0.022 *p*=1.00	*ts*=0.022 *p*=1.00	*ts*=0.022 *p*=1.00	*ts*=0.045 *p* =1.00	*ts*=0.022 *p*=1.00	*ts*=0.022 *p*=1.00	*ts*=0.022 *p* =1.00	*ts*=0.022 *p*=1.00
Pre-GFC									
ECP(*CvM*)	*ts*=0.003 *p*=1.00	*ts*=0.003 *p* =1.00	*ts*=0.003 *p*=1.00	*ts*=0.001 *p*=1.00	*ts*=0.001 *p* =1.00	*ts*=0.001 *p*=1.00	*ts*=0.001 *p*=1.00	*ts*=0.001 *p* =1.00	*ts*=0.001 *p*=1.00
ECP2(*CvM*)	*ts*=0.001 *p*=1.00	*ts*=0.001 *p*=1.00	*ts*=0.001 *p*=1.00	*ts*=0.001 *p*=1.00	*ts*=0.001 *p* =1.00	*ts*=0.001 *p*=1.00	*ts*=0.001 *p*=1.00	*ts*=0.001 *p* =1.00	*ts*=0.001 *p*=1.00
ECP (*KS*)	*ts*=0.607 *p*=0.28	*ts*=0.849 *p*=0.27	*ts*=0.824 *p*=0.34	*ts*=0.391 *p*=0.24	*ts*=0.290 *p* =0.12	*ts*=0.315 *p*=0.24	*ts*=0.117 *p*=1.00	*ts*=0.117 *p* =1.00	*ts*=0.117 *p*=1.00
ECP2(*KS*)	*ts*=0.039 *p*=1.00	*ts*=0.039 *p*=1.00	*ts*=0.039 *p*=1.00	*ts*=0.039 *p*=1.00	*ts*=0.039 *p* =1.00	*ts*=0.039 *p*=1.00	*ts*=0.039 *p*=1.00	*ts*=0.039 *p* =1.00	*ts*=0.039 *p*=1.00
GFC									

ECP(*CvM*)	*ts*=0.012 *p*=0.77	*ts*=0.004 *p*=1.00	*ts*=0.003 *p*=1.00	*ts*=0.007 *p*=1.00	*ts*=0.004 *p* =1.00	*ts*=0.004 *p*=1.00	*ts*=0.004 *p*=1.00	*ts*=0.001 *p* =1.00	*ts*=0.005 *p*=1.00
ECP2(*CvM*)	*ts*=0.001 *p*=1.00	*ts*=0.001 *p*=1.00	*ts*=0.001 *p*=1.00	*ts*=0.001 *p*=1.00	*ts*=0.001 *p* =1.00	*ts*=0.001 *p*=1.00	*ts*=0.001 *p*=1.00	*ts*=0.001 *p* =1.00	*ts*=0.001 *p*=1.00
ECP (*KS*)	*ts*=1.010 *p*=0.395	*ts*=0.770 *p*=0.22	*ts*=0.367 *p*=0.78	*ts*=0.754 *p*=0.53	*ts*=0.435 *p* =0.66	*ts*=0.550 *p*=0.40	*ts*=0.902 *p*=0.07	*ts*=0.195 *p* =0.99	*ts*=0.851 *p*=0.07
ECP2(*KS*)	*ts*=0.077 *p*=1.00	*ts*=0.039 *p*=1.00	*ts*=0.076 *p*=1.00	*ts*=0.039 *p*=1.00	*ts*=0.039 *p* =1.00	*ts*=0.039 *p*=1.00	*ts*=0.902 *p*=0.07	*ts*=0.039 *p* =1.00	*ts*=0.039 *p*=1.00
Post-GFC									
ECP(*CvM*)	*ts*=0.002 *p*=1.00	*ts*=0.001 *p*=1.00	*ts*=0.002 *p*=1.00	*ts*=0.003 *p*=1.00	*ts*=0.004 *p* =1.00	*ts*=0.005 *p*=1.00	*ts*=0.001 *p*=1.00	*ts*=0.002 *p* =1.00	*ts*=0.001 *p*=1.00
ECP2(*CvM*)	*ts*=0.001 *p*=1.00	*ts*=0.001 *p*=1.00	*ts*=0.001 *p*=1.00	*ts*=0.001 *p*=1.00	*ts*=0.001 *p* =1.00	*ts*=0.001 *p*=1.00	*ts*=0.001 *p*=1.00	*ts*=0.001 *p* =1.00	*ts*=0.001 *p*=1.00
ECP (*KS*)	*ts*=0.431 *p*=0.055	*ts*=0.131 *p*=1.00	*ts*=0.304 *p*=0.43	*ts*=0.394 *p*=0.305	*ts*=0.397 *p* =0.57	*ts*=0.468 *p*=0.245	*ts*=0.117 *p*=1.00	*ts*=0.470 *p* =0.21	*ts*=0.139 *p*=1.00
ECP2(*KS*)	*ts*=0.039 *p*=1.00	*ts*=0.039 *p*=1.00	*ts*=0.039 *p*=1.00	*ts*=0.039 *p*=1.00	*ts*=0.039 *p* =1.00	*ts*=0.039 *p*=1.00	*ts*=0.039 *p*=1.00	*ts*=0.039 *p* =1.00	*ts*=0.039 *p*=1.00

Notes: The abbreviations *p* and *ts* stand for the p-value and the t-statistic. The *ECP* and *ECP2* refer to the empirical copula processes. The *CvM* and *KS* stand the Cram von Mises and Kolmogorov-Smirnov test statistics.

The identification of the vine copula model that provides the best fit is ultimately based on the resulting p-values from the goodness-of-fit testing. The smaller the p-values are, the larger the distance between the fitted parametric vine copula model and the empirical distribution of the multivariate dependence structure. The larger the p-values are, the smaller the distance between the fitted parametric vine copula model and the empirical distribution of the multivariate dependence structure. When deciding on the vine model that best accounts for the dependence of the assets, a particular weight is given to the p-values from the full sample period's goodness-of-fit testing. The reason for this is that the goodness-of-fit testing has been found to best perform when the number of observations is large (Schepsmeier, 2013, 2014; Panchenko, 2005; Genest et al., 2009) for further details on the goodness of fit tests).

According to Table 7, the p-values resulting from the goodness of fit testing of the retail portfolio for the r-vine are in general (i.e., taking into account all four period scenarios) larger than those resulting from the goodness of the fit testing for the c-vine and d-vine. The same applies to the gold portfolio, with the r-vine best capturing its multivariate dependence structure. Also, the p-values resulting from the goodness of fit testing of the manufacturing portfolio for the d-vine are in general larger than those resulting from the goodness of fit testing for the r-vine and c-vine.

Hence, the alternative hypothesis is accepted. As a result, the goodness of fit testing confirms the copula counting technique findings about the r-vine and d-vine as the models that most accurately approximate the dependence structure of the gold, retail and manufacturing portfolios.

6. Conclusion

This article applies the pair vine copula models to relatively large sector portfolios to address the complex issue of dependence risk modeling. We extend the related literature by providing an in-depth and comprehensive analysis of the portfolios' multivariate dependence structure and dependence risk dynamics by means of a "copula counting technique". In doing so, new insights and useful information are provided that could be used to develop dependence risk and investment risk-adjusted strategies for investment, rebalancing and hedging that more adequately account for downside risk in various market conditions.

By considering three 20-asset portfolios from the retail, manufacturing and gold-mining equity sectors of the Australian stock market, in the context of the 2008-2009 global financial crisis and other period scenarios revolving around it, we find the retail portfolio is less dependence risky than the manufacturing portfolio in the crisis period. This is due to the economic linkages the retail sector has with the overall Australian resources sector and the more volatile economic linkages the overall resources sector has with the manufacturing sector (Pilat et al., 2006). The benchmark gold-mining portfolio is found to be less dependence risky than the retail and significantly less dependence risky than the manufacturing in similar market conditions. The relative good performance of the gold-mining sector relative to the retail and manufacturing sectors during crisis periods makes the gold-mining stocks preferable. On the other hand, the performance of the retail and manufacturing sectors is dependent on the performance of the gold-mining sector in those turbulent times. The retail and gold-mining stocks are observed to display a higher propensity to yield positively skewed returns in the crisis period, relative to the manufacturing stocks. The r-vine and d-vine are found to best capture the multivariate dependence structure of the retail and gold portfolios, and the manufacturing portfolio, respectively.

Considering the specific risk characteristics of the modeled portfolios, investments in the retail and gold-mining equity sectors could be used to hedge investment positions in alternative sectors (e.g. the manufacturing sector) that have higher dependence risk and negatively skewed return behavior during crisis periods. As part of a risk management framework or a hedging strategy, both sectors could in general be used to manage downside risk. Also, based on both portfolios dependence risk differences, investments in the retail sector could be used to hedge an investment position in the gold-mining sector as the financial stock markets transit from a crisis to a non-crisis period. In terms of investment and downside risk management during crisis periods, the gold sector is preferable to the retail sector and both sectors are preferable to the manufacturing sector. Portfolio and risk managers and those who follow the trends of the Australian retail, manufacturing and gold-mining sectors may find our empirical results useful for trading and hedging purposes in order to design dependence risk-adjusted resource management frameworks and for complying.

References

Aas, K., Czado, C., Frigessi, A., Bakken, H., 2009. Pair-copula constructions of multiple dependence. Insurance: Mathematics and Economics Journal 44(2), 182–198.

Aloui, R., Ben Aissa, M.S., Nguyen, D.K., 2011. Global financial crisis, extreme interdependences, and contagion effects: the role of economic structure? Journal of Banking and Finance 35, 130–141.

Allen, D.E., Ashraf, M.A., McAleer, M., Powell, R.J., Singh, A.K., 2013. Financial dependence analysis: applications of vine copulae. Statistica Neerlandica 67(4), 403-435.

Arreola-Hernandez, J., 2014. Are oil and gas stocks from the Australian market riskier than coal and uranium stocks? Dependence risk analysis and portfolio optimization. Energy Economics 45, 528-536.

Bekiros, S., Arreola-Hernandez, J., Hammoudeh, S., Khuong-Nguyen, D., 2015. Multivariate dependence risk and portfolio optimization: an application to mining stock portfolios. Resources Policy, 46, 1-11.

Australian Retailers Association, 2014. Financial system inquiry, Canberra, Australia.

Australian Government Productivity Commission, 2011. Economic structure and performance of the Australian retail industry.

Bank for International Settlements, 2009. The international financial crisis: timeline, impact and policy responses in Asia and the Pacific. BIS papers, 52, 21-82.

Baur, D.G., 2012. Financial contagion and the real economy. Journal of Banking and Finance 36(10), 2680-2692.

Baur, D.G., McDermott, T.K., 2009. Is gold a safe haven? International evidence. Journal of Banking & Finance 34(8), 1886-1898.

Baur, D. G., Lucey, B. M., 2010. Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. Financial Review 45(2), 217-229.

Bedford, T., Cook, R.M., 2002. Vines- a new graphical model for dependent random variables. Annals of Statistics 30, 1031–1068.

Bedford, T., Cooke, R.M., 2001. Probability density decomposition for conditionally dependent random variables modelled by vines. Annals of Mathematics and Artificial Intelligence 32, 245–268.

Bingham, F., Perkins, B., 2012. Australia's coal and iron ore exports 2001 to 2011. Department of Foreign Affairs and Trade: Economic Advocacy & Analysis Branch.

Brechmann, E.C., Schepsmeier, U., 2011. Modelling dependence with c and d vine copulas: The R-package C-D vine. Journal of Statistical Software 52(3), 1-26.

Brechmann, E.C. and Czado, C., 2012. COPAR - Multivariate Time Series Modeling Using the COPula AutoRegressive Model. Munich University of Technology, Preprint arXiv:1203.3328.

Chollete, L., Heinen, A., and Valdesogo, A., 2009. Modelling international financial returns with a multivariate regime switching copulas. Journal of Financial Econometrics 7, 437-480.

Collins, T., 2013. Australia's gold industry: trade, production and outlook. Department of Foreign Affairs and Trade: Economic Advocacy & Analysis Branch, 1-5.

Common Wealth Treasury, 2012. The Australian dollar and the manufacturing sector. Canberra, Australia.

Cooke, R.M., 1997. Markov and entropy properties of tree- and vine-dependent variables, in: Proceedings of the ASA Section on Bayesian Statistical Science, 1-10.

Czado, C., 2010. Pair-copula constructions of multivariate copulas. In “Copula Theory and Its Applications”, P. Jaworski et al. (Eds.), 93-109. Springer: Berlin Heidelberg.

Czado, C., Schepsmeier, U., Min, A., 2012. Maximum likelihood estimation of mixed c-vines with application to exchange rates. Statistical Modelling 12(3), 229–255.

Czado, C., Brechmann, C., Gruber, L., 2013. Selection of vine copulas. In P. Jaworski, F. Durante and W. K. Härdle (Eds.), Copulae in Mathematical and Quantitative Finance, Springer.1-20.

Delloite, 2013. Global Powers of Retailing: Retail and beyond. Perth, Australia.

Delloite, 2011. The structure and performance of the Australian retail industry. Perth, Australia.

Department of Innovation, Industry, Science and Research, 2010. Manufacturing Sector: overview of structural change- Industry brief 2008-2009. Sydney, Australia.

Department of Industry, 2014. Australian Industry Report. Canberra, 1-220.

Dissmann, J., Brechmann, E.C., Czado, C., Kurowicka, D., 2013. Selecting and estimating regular vine copulae and application to financial returns. Computational Statistics & Data Analysis 59, 52-69.

Dissmann, J.F., 2010. Statistical inference for regular vines and application, Diploma Thesis, Technische Universitat Munchen.

Federal Reserve Bank of St. Louis, 2009. The Financial Crisis: A Timeline of Events and Policy Actions. http://timeline.stlouisfed.org.

Genest, C., Remillard, B., Beaudoin, D., 2009. Goodness-of-fit tests for copulas: A review and a power study. Insurance: Mathematics and Economics 44(2), 199-213.

Green, R. and Roos, G., 2012. Australia’s Manufacturing Future. Adelaide, Australia.

Heinen, A., Valdesogo, A., 2009. Asymmetric CAPM dependence for large dimensions: The canonical vine autoregressive copula model. CORE Discussion Paper No. 69.Kakouris, I., Rustem, B., 2013. Robust portfolio optimization with copulas. European Journal of Operational Research. In Press, Accepted Manuscript.

Hernandez, J.A., 2015. Vine copula modelling of dependence and portfolio optimization with application to mining and energy stock return series from the Australian market. Doctoral Dissertation, Edith Cowan University, Australia.

Joe, H., 1997. Multivariate models and dependence concepts. Chapman & Hall, London.

KordaMentha, 2013. Australian manufacturing: redefining manufacturing. Perth, Australia.

Kurowicka, D., Cooke, R.M., 2006. Uncertainty analysis with high dimensional dependence modelling. Chichester: John Wiley.

Kryger, A., 2014. Performance of the manufacturing industry: a quick guide. Parliament of Australia: Department of Parliamentary Services, Canberra, November, 1-5.

Low, R.K.Y., Alcock, J., Faff, R., Brailsford, T., 2013. Canonical vine copulas in the context of modern portfolio management: Are they worth it? Journal of Banking and Finance 37(8), 3085-3099.

Mehmedovic, S. Pallant J. and Pacini E., 2011. Australian Retail Snapshot. The Australia center for retail studies. Monash University, Melbourne, Australia.

Min, A., Czado, C., 2010. Bayesian inference for multivariate copulas using pair-copula constructions. Journal of Financial Econometrics 8 (4), 1-23.

National Australia Bank, 2012. Sector Insights: Manufacturing. Canberra, Australia.

Nikoloulopoulos, A.K., Joe, H., Li, H., 2012. Vine copulas with asymmetric tail dependence and applications to financial return data. Computational Statistics & Data Analysis 56(11), 3659-3673.

Panchenko, V., 2005. Goodness of fit testing for vine copulas. Physica A: Statistical Mechanics and its Applications 355(1), 176-182.

Patton, A., 2012. A review of copula models for economic time series. Journal of Multivariate Analysis 110, 4-18.

Pilat, D., Cimper, A., Olsen, K.B., Webb, C., 2006. The changing nature of manufacturing in OECD economies. OECD Science, Technology and Industry Working Papers. DOI: 10.1787/308452426871.

Reboredo, J.C., 2013. Is gold a safe haven or a hedge for the US dollar? Implications for risk management. Journal of Banking and Finance 37(8), 2665-2676.

Reboredo, J.C. y Rivera-Castro, M.A., 2014. Gold and exchange rates: downside risk and hedging at different investment horizons. International Review of Economics and Finance 34, 267-279.

Savills Research, 2014. Australian Retail Market. Perth, Australia.

Schepsmeier, U., 2013. A goodness-of-fit test for regular vine copula models. http://arXiv preprint arXiv:.org/abs/1306.0818.

Schepsmier, U., 2014. Efficient goodness-of-fit tests in multidimensional vine copula models. http://arXiv:1309.5808.

Sklar, A., 1959. Fonctions de répartition and dimensions et leurs marges. Institut de Statistique de l'Université de Paris, 8, 229–231.

Appendix

Table A1: Descriptive statistics of the gold, retail and manufacturing stocks

Gold stock codes	μ	σ^2	K	SK	Retail stock codes	μ	σ^2	K	SK	Manufacturing stock codes	μ	σ^2	K	SK
SBMX	0.07	0.18	4.56	-0.05	CCLX	0.03	0.03	5.15	-0.17	SFCX	-0.06	0.04	16.39	-1.38
NWRX	-0.02	0.44	26.64	-1.10	HILX	-0.07	0.06	6.78	0.14	BLDX	-0.04	0.05	3.78	-0.14
NSTX	0.11	0.37	10.66	0.16	GWAX	-0.02	0.05	2.77	0.14	BKWX	-0.01	0.03	7.57	0.26
SHKX	-0.17	0.30	4.29	0.47	MTUX	0.12	0.10	4.69	0.50	CSRX	-0.07	0.05	7.69	-0.68
DEGX	-0.18	0.32	11.40	1.08	MTSX	0.01	0.02	4.38	-0.14	JHXX	0.01	0.06	4.83	0.42
RSGX	0.01	0.15	5.75	-0.23	WOWX	0.03	0.02	5.57	-0.33	OLHX	-0.13	0.15	23.73	-1.04
AXMX	-0.22	0.44	16.79	-0.15	ARPX	0.05	0.03	5.47	0.10	CKLX	-0.01	0.06	5.08	0.10
ORNX	-0.16	0.36	6.61	-0.03	CCVX	0.04	0.10	5.38	-0.21	ANNX	0.02	0.03	2.50	0.33
RCFX	-0.14	0.61	5.67	0.65	DJSX	0.00	0.05	6.22	-0.26	SDIX	-0.13	0.17	12.64	0.45
EXMX	-0.17	1.78	13.85	0.02	DLCX	-0.07	0.60	9.17	0.33	SOMX	-0.08	0.37	10.52	0.18
TAMX	-0.05	0.26	17.94	0.85	HVNX	-0.02	0.05	4.05	0.16	UCMX	-0.17	0.25	17.43	-0.60
GLNX	-0.41	1.14	563.41	-17.93	JBHX	0.04	0.06	4.72	-0.11	FWDX	0.02	0.04	6.85	0.04
MOYX	-0.15	0.45	22.31	0.11	RCG	0.00	0.21	8.64	0.20	FANX	-0.03	0.06	9.59	-0.44
EVNX	0.00	0.32	10.79	0.74	SFHX	-0.04	0.10	5.17	0.48	KRSX	-0.08	0.15	11.24	-0.43
AUZX	-0.14	2.15	16.55	-0.00	SULX	0.05	0.06	6.68	-0.25	ASBX	-0.01	0.06	8.43	0.46
HEGX	-0.09	0.29	3.09	0.45	WESX	-0.01	0.03	8.31	-0.39	MHIX	0.00	0.13	23.90	-0.03
KMCX	-0.21	0.53	45.01	-2.27	FANX	-0.03	0.06	9.59	-0.44	CSLX	0.07	0.03	2.73	0.04
IRCX	0.01	0.28	10.24	0.70	GZLX	-0.03	0.05	17.29	-0.80	IDTX	-0.12	0.10	11.57	-0.13
HAOX	-0.02	0.67	18.06	1.85	FLTX	0.00	0.07	9.55	0.07	CDAX	-0.01	0.08	11.39	0.69
CTOX	-0.02	0.19	27.91	2.05	JETX	-0.02	0.10	5.78	0.12	LGDX	-0.03	0.18	90.45	-4.44

Notes: This table reports the descriptive statistics of the gold-mining, retail and manufacturing portfolios. The abbreviations μ, σ^2, K and SK stand for mean, variance, kurtosis and skewness.

The stock portfolios' descriptive statistics indicate that in the gold portfolio ST. BARBARA (SBMX), NORTHERN STAR (NSTX), RESOLUTE MINING (RSGS) and INTERMIN RESOURCES (IRCX) have the largest mean returns relative to risk. In the retail portfolio, COCA-COLA (CCLX), M2 TELECOM (MTUX), WOOLWORTHS (WOWX) and ARB (ARPX) offer the best risk-return trade-offs. In the manufacturing portfolio CSL (CSLX), FLEETWOOD (FWDX), ANSELL (ANNX) and JAMES HARDIE (JHXX) offer the best risk-return trade-offs.