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RESEARCH ARTICLE

PANEL COINTEGRATION FOR COPULA-BASED MULTIVARIATE MODELS TO JUSTIFY INTERNATIONAL R&D SPILLOVERS

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ABSTRACT

In this paper we develop a new methodology to measure and to analysis panel Cointegration. Our new approach proposes one copula-based test for testing cross-sectional independence of panel models. To justify international R&D Spillover, we adopt a copula based multivariate model as a new approach, it is important to test the cross-sectional dependence in panel models because the existence of cross-sectional dependence will invalidate conventional tests such as t-tests and F-tests which use standard covariance estimators of parameters estimators. Estimation methods depend on the existing of cross-sectional in the error of panel models.

INTRODUCTION

Many results on nonparametric density estimation are based on the assumption that the support of the random variable of interest is the real line. However, in applications, data are often bounded with a possible high concentration close to the boundary. For example, in labor economics, the income distribution for a specific country is bounded at the minimum wage. Usual nonparametric density estimation techniques, for example the well known Gaussian kernel, for these kinds of data produce inconsistent results because the kernel allocates weight outside the support implying an under estimation of the underlying density in the boundary. This boundary bias problem is well documented in the univariate case. The first technique to resolve this problem is proposed by Schuster (1985) suggesting the reflection method. Lejeune and Sarda (1992), Jones (1993) Jones and Foster (1996), Muller (1991), and Rice (1984) use flexible kernels called boundary kernels instead of the usual fixed kernels. Marron and Ruppert (1994) recommend transforming data before applying the standard kernel. Chen (2000) proposes a gamma kernel estimator, Bouezmarni and Scaillet (2005) and Bouezmarni and Rombouts (2006) investigate the properties of a gamma estimator in respectively a mean absolute deviation and a time series framework.

In general, the univariate framework is only a first step towards multivariate density estimation in order to explain links between variables the supports of some are potentially bounded. The problem of inconsistent density estimation carries over (and becomes even more substantial) in the case of multivariate bounded random variables. For the same reason as above, the multivariate Gaussian kernel density estimator is not suitable for these kinds of random variables. An additional problem with nonparametric multivariate density estimation is that the rate of convergence of the mean integrated squared error increases with the dimension. This is the well known curse of dimensionality problem. To date, the boundary and the curse of dimension problems have not been addressed simultaneously. For example, Muller and Stadtmuller (1999) propose a multivariate estimator without a boundary problem but with a problem of curse of dimension. Liebscher (2005) puts forward a semi-parametric estimator based on copulas and on the standard kernel estimator for the marginal densities which solves the curse of dimension problem but not the boundary problem.

This paper proposes a multivariate semi parametric density estimation method which is robust to both the boundary and the curse of dimension problem. The estimator combines gamma or local linear kernels the support of which matches that one of the underlying multivariate density, and semi-parametric

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copulas. This leads to an estimator which is easy to implement. We derive asymptotic properties such as the mean integrated squared error, uniform strong consistency and asymptotic normality. In the simulations we compare the finite sample performance of the (modified) gamma and the local linear estimator for the marginal densities using the Gaussian and the Gumbel-Hougaard copula. We find that the univariate least squares cross validation technique to choose the bandwidths for the marginal kernel density estimators works successfully. Therefore, bandwidth selection for our estimator can be done in a computational straight forward manner.

The simulations reveal also that for data without a boundary problem our estimator performs very well.

Examples of multivariate positive data abound in finance and economics. Cho (1998) investigates whether ownership structure affects investment using variables such as capital expenditures, and research and development expenditures sampled from the 1991 Fortune 500 manufacturing firms. Grullon and Michaely (2002) study the relationship over time between dividends and share repurchases conditional on the market value and the book value of assets for US corporations. In our application we estimate the joint density of international R&D spillover and the economic growth. The data come from 32 countries observed in1990 to 2013. We use the Gumbel-Hougaard copula as suggested by the simulation results.

This paper considers tests of cross-sectional dependence using copulas in panel models. It is important to test the cross-sectional dependence in panel models because the existence of cross- sectional dependence will invalidate conventional tests such as t-tests and F-tests which use standard covariance estimators of parameter estimators. Moreover, the choice of estimation methods may depend upon whether there exists cross-sectional dependence in the errors of panel models. When the errors are cross-sectionally dependent in panel data models, for example, the computation of MLE and GMM could be rather complicated, and the feasible GLS estimator will be invalid or have to be modified substantially.

The organization of the paper is as follows. In Section 2, we describe a new framework based on copula. The panel models and copulas is presented in Section 3. we discuss the copula-based tests in panel data for international R&D spillover in section 4. Section 5 presents the conclusion.

A new framework based on copulas

A brief introduction to copulas

Copulas have been introduced by Sklar [1959] to study probabilistic metric spaces. They have been rediscovered on several occasions by statisticians in the seventies (see Deheuvels [1978], Galambos [1978] and Kimeldorf and Sampson [1975]). However, the first statistical applications of copulas appear only in the middle of the eighties. In this paragraph, we adopt a simplified point of view to present copulas, and we invite the reader to consult the book of Nelsen [1998] to have a more rigourous presentation. Moreover, we restrict to the two-dimensional case, but generalization to higher dimensions is straightforward. Copula method has been widely discussed in literature, e.g., Frees and Valdez (1998), Cherubini *et al.* (2004), Oakes (1994), Genest *et al.* (1995), Shih and Louis (1995), Joe and Xu (1996), Patton (2002b), Chen and Fan (in press, 2006a, 2006b), to name a few. Moreover, the copula method was also applied to model correlation structure or test dependence between time series data, e.g., Patton (2002a, b), Chen, Fan, and Patton (2004). Patton (2002a) uses the concept of conditional copula to model the time-varying correlation of exchange rates. Chen, Fan, and Patton (2004) apply integral transform and kernel estimation to test the dependence between financial time series. Nonetheless, there is still no research, as far we know, about using copulas to test the cross-sectional dependence in panel models.

Copulas

At the beginning of this section, we give the general definition of the copula

Definition 1 A d-dimensional copula is a multivariate cumulative distribution function $C : [0,\ 1]^d \rightarrow [0,\ 1]$, whose margins have the uniform distribution on the interval $[0,\ 1]$.

The following theorem is a very significant result in the copula theory.

Theorem 1 (Sklar's theorem). Let F denote a d-dimensional distribution functions with marginal distribution functions $F_{X_1},...,F_{X_d}$. Then, there exists a copula C, such that

$$F(x_1,...,x_d) = C\left(F_{X_1}(x_1),...,F_{X_d}(x_d)\right) \quad \textit{for any} \quad (x_1,...,x_d) \in R^d.$$

In addition, we have that, if $F_{X_1},...,F_{X_d}$ are continuous, then the copula C is a unique one.

Conversely, if C is a copula and $F_{X_1},...,F_{X_d}$ are distribution functions, then the function F, defined by (2), is the joint distribution function with marginal distribution functions $F_{X_1},...,F_{X_d}$.

In our considerations, we restrict ourselves to the case of 2-dimensional (bivariate) copulas. Below, we present the four families of copulas used in our paper, namely: the bivariate normal copula, the bivariate Student t-copula, the bivariate Plackett copula and the bivariate Clayton copula.

The bivariate normal copula

The bivariate normal copula is the function of the form:

$$C(u_1,u_2;\circ) = \int_{-\infty}^{\Phi^{-1}(u_1)} \int_{-\infty}^{\Phi^{-1}(u_2)} \frac{1}{2\text{®}\sqrt{1-\circ^2}} \exp\left\{-\frac{r^2 - 2\circ rs + s^2}{2(1-\circ^2)}\right\} drds,$$

Where ρ is the linear correlation coefficient between the two random variables and Φ^{-1} stands for the inverse of the univariate standard normal distribution function.

The bivariate Student t-copula

The bivariate normal copula is the following function:

$$C(u_1,u_2;\rho,v)=\int_{-\infty}^{t_v^{-1}(u_1)}\int_{-\infty}^{t_v^{-1}(u_2)}\frac{1}{2\pi\sqrt{1-\rho^2}}\exp\left\{1+\frac{r^2-2\rho rs+s^2}{v(1-\rho^2)}\right\}^{-(v+2)/2}drds,$$

Where ρ is the linear correlation coefficient between the two random variables and t_v^{-1} denotes the inverse of the univariate Student-t distribution function with v degrees of freedom.

The bivariate Plackett copula

The bivariate Plackett copula is the function defined by

$$C(u_1,u_2;\theta)=\begin{cases}\frac{1}{2(\theta-1)}\left[1+(\theta-1)(u_1+u_2)-\left([1+(\theta-1)(u_1+u_2)]^2-4u_1u_2\theta(\theta-1)\right)^{1/2}\right] & for\ \theta\neq 1,\\ u_1u_2 & for\ \theta=1,\end{cases}$$

Where θ stands for the given parameter value.

The bivariate Clayton copula

The following function is called the bivariate Clayton (or Cook Johnson) copula:

$$C(u_1,u_2;\theta)=\max\left\{\left(u_1^{-\theta}+u_2^{-\theta}-1\right)^{-1/\theta},0\right\},$$

Where θ denotes the fixed parameter value.

The model and test statistics

Consider the following panel data regression model, see Baltagi (2001):

$$y_{it}=\beta' x_{it}+\mu_i+\lambda_t+v_{it}$$

i= 1,…………, N et t = 1,……………, T (1)

Where yit is a scalar, xit is a p×1 vector of regressors that may contain lagged dependent variables, β is a p×1 vector of slope parameters, μi is the individual effect, λ_t is the time effect, and v_{it} is the error term. We allow for fixed or random effects. The slope parameter β is often of interest and it can be estimated, e.g., by the within estimator

$$\hat{\beta}=\left[\sum_{i=1}^{n}\sum_{t=1}^{T}\tilde{x}_{it}\tilde{x}'_{it}\right]^{-1}\left[\sum_{i=1}^{n}\sum_{t=1}^{T}\tilde{x}_{it}\tilde{y}'_{it}\right] \quad (2)$$

Where

$$\bar{x}_{i.}=\frac{1}{T}\sum_{i=1}^{T}x_{it}$$

$$\bar{x}_{.t}=\frac{1}{n}\sum_{i=1}^{N}x_{it}$$

And $\bar{x}=\frac{1}{n}\frac{1}{T}\sum_{i=1}^{N}\sum_{i=1}^{T}x_{it}$

The variables $\tilde{y}'_{it}$, $\bar{y}_{i.}$, $\bar{y}_{.t}$, and $\bar{y}_t$, are defined similarly. For interval estimation and hypothesis testing, one often uses the standard covariance estimator of $\hat{\beta}$, where $\hat{\sigma}_v^2$ is an estimator for σ_v

$$\hat{\Omega}_{\hat{\beta}}=\hat{\sigma}_v^2\left(\sum_{i=1}^{n}\sum_{t=1}^{T}\tilde{x}_{it}\tilde{x}'_{it}\right)^{-1}$$

of $\hat{\beta}$, where $\hat{\sigma}_v^2$ is an estimator for σ_v^2 =Var(v_{it}). This estimator is valid when {v_{it}} in Eq. (1) is cross-sectionally uncorrelated, among other things. The existence of cross-sectional dependence of any form, however, will generally invalidate the covariance estimator and related inference. In particular, conventional t- and F-tests will be misleading.

We are interested in testing whether the error process {v_{it}} is cross-sectionally dependent. To test the null hypothesis, we will

Examine the cross-sectional dependence in the demeaned estimated residual $\hat{v}_{it}=\hat{u}_{it}-\hat{u}_{i.}-\hat{u}_{.t}+\bar{u}$, where

$$\hat{u}_{it}=y_{it}-x'_{it}\hat{\beta}$$

$$\hat{u}_{i.}=\frac{1}{T}\sum_{i=1}^{T}\hat{u}_{it}$$

$$\hat{u}_{.t}=\frac{1}{n}\sum_{i=1}^{N}\hat{u}_{it}$$

$$\bar{u}=\frac{1}{n}\frac{1}{T}\sum_{i=1}^{N}\sum_{i=1}^{T}\hat{u}_{it}$$

And $\hat{\beta}$ is a consistent estimator for β under the null of no cross-sectional dependence. When $\hat{\beta}$ is the within estimator in Eq. (2), v̂it is the usual within residual in the literature.

Let v_t=(v_{1t} ,…, v_{nt})′. For each t, we assume that {v_t} has a continuous joint distribution H(v_{1t} ,…, v_{nt}) and continuous marginal distribution Fi(v_i) for i=1,…, n. By Sklar's (1959) ***theorem, 1*** there exists a unique copula function

$$H(v_{1t},\ldots,v_{nt})=C(F_1(v_{1t}),\ldots,F_n(v_{nt}))$$

The essence of copulas is that one can always model any multivariate distribution by modeling its marginal distributions and its copula functions separately, where the copula captures all the scale-free dependence in the multivariate distribution. Thus, a copula is a multivariate distribution function that connects marginal distributions so that to exactly form the joint distribution.

A copula thus completely parameterizes the entire dependence structure between two or more random variables. It is important to note that a given distribution function H defines only one set of marginal distribution functions Fi, i=1,…, n, where given marginal distributions do not determine a unique joint distribution.

To connect copulas to likelihood-based model, let h and c be the derivatives of the distributions H and C, respectively. Then

$$h(v_{1t},\ldots\ldots,v_{nt}) = \frac{\partial^{n} H(v_{1t},\ldots\ldots,v_{nt})}{\partial v_{1t}\ldots\ldots\partial v_{nt}}$$

$$= \frac{\partial^{n} C(F_{1}(v_{1t}),\ldots\ldots\ldots,F_{n}(v_{nt}))}{\partial v_{1t}\ldots\ldots\partial v_{nt}}$$

$$= \frac{\partial^{n} C((U_{1t}),\ldots\ldots\ldots,(U_{nt}))}{\partial v_{1t}\ldots\ldots\partial v_{nt}} \vdots U_{it} = F_{i}(v_{it}) \prod_{i=1}^{n} f_{i}(v_{it})$$

$$c(F_{1}(v_{1t}),\ldots\ldots\ldots,F_{n}(v_{nt})) \prod_{i=1}^{n} f_{i}(v_{it})$$

Panel Cointegration Copula-Based Tests for international R&D cooperation

In the literature, the estimation for the copula parameter can be categorized into three types: exact maximum likelihood estimation (MLE), two-step MLE, and semi parametric two-step estimation. In this paper, we use the semi parametric two-step approach.

Table 1. Peptidyl and peptidomimetic P_1-argininal derivatives **2a-t** produced via Scheme 1

7	Conditions	Ratio ~:	Yield %
1.0 equiv	TfOH (0.04 equiv), toluene, −20 °C	1:1	72
3.0 equiv	TfOH (0.01 equiv), toluene, −20 °C	2:3	89
3.0 equiv	TMSOTf (0.01 equiv), Et_2O, −20 °C	7:3	88
3.0 equiv	TMSOTf (0.01 equiv), Et_2O, −30 °C	11:0	95

[a]The reaction was conducted in anoxic conditions.

CONCLUSION

This paper presents the copula-based tests to detect cross-sectional dependence in panel models. Some commonly used copula families and their related properties are provided in

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