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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 $F_{X_1},\ldots,F_{X_d}$. Then, there exists a copula C, such that

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

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

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

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:

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

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), v˜it is the usual within residual in the literature.

Let $v_t=(v_{1t},\ldots,v_{nt})'$. For each t, we assume that {v_t} has a continuous joint distribution H(v_{lt} ,…, 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

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

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

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

$$= \frac{\partial^n C(F_1(v_{1t}),\ldots,F_n(v_{nt}))}{\partial v_{1t}\ldots\partial v_{nt}}$$

$$= \frac{\partial^n C((U_{1t}),\ldots,(U_{nt}))}{\partial v_{1t}\ldots\partial v_{nt}} : U_{it} = F_i(v_{it})\prod_{i=1}^{n} f_i(v_{it})$$

4. 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.

By the nature of our collected data, we face sample selection problem as often occurring in the fields of economics. However, several methods have been introduced but the debate is still open for researchers to find the best procedure which will obtain robust estimates from the sample selection model. In general, the two-step estimators proposed by Heckman (1979) and the maximum likelihood (ML) estimators are accepted as the most efficient estimators, as long as the underlying models are correctly specified.

Moreover, these estimators can be derived only under a limited number of distributions and require specified joint distribution. The Heckman model and other empirical studies (e.g. Lee (1983), Vella and Verbeek (1999) Husted et.al (2001), and Dustmann and Rochina-Barrachina (2007)) impose bivariate normality on both margins, with each margin itself being normally distributed. However, this assumption can often be seen as unrealistic.

To relax the normality assumption, a obvious trend of research has focused on semi-parametric or non-parametric methods (Wooldridge (1995), Kyriazidou (1997)) which does not require strict distribution assumptions. However, semi-parametric or non-parametric methods impose some costs, for example, the intercept of the outcome equation is not identified which, in an economic context, the intercept is important to identify the effect of policy implications. Another problem is estimation of the covariance matrix of the parameters is more demanding than in the parametric case (see Vella (1998)).

Moreover, Smith (2003) suggested the copula approach to carry out sample selection and indicated a special case of copulas, namely the Archimedean copulas, which are easy to implement and quite flexible to fit in to a variety of distributional shapes. Genius and Strazzera (2008) also applied the copula approach to sample selection modeling. They showed the copula approach works when the assumption of normality of the joint distribution is patently violated.

Additionally, we use panel data which or longitudinal where each unit of individual is observed more than one time. The advantage of panel data across cross-sectional data is the presence of unobserved individual-specific effect in the equation of interest. Economic theory often suggests containing an unobserved heterogeneity which correlated with the model regressors. If unobserved individual specific effects affect the outcome variable, and are correlated with the model regressors, simple regression analysis does not identify the parameters of interest. The problem of unobserved individual-specific effects may be solved by using panel data or longitudinal where each unit of individual is observed more than one time. There are numerous of estimators which are available for estimating the parameters of panel data models providing a solution to this latter problem (see Hsiao (1986) and Baltagi (2008) for overviews).

Therefore, the objective of this chapter is to apply the copula approach to a sample selection modeling of panel data and to construct a model of economic output in developed countries for which there currently exists a sample selection bias, and to attempt to compare results of the Maximum Likelihood under the assumptions of normality and those obtained from the copula approach.

4.1. Data

The study is based on an unbalanced panel data set covering 22 developed countries over the period of 2001 to 2014. The countries are Australia, Austria, Canada, Moroco, Egypt, Denmark, Finland, Hong Kong, Iceland, Israel, Japan, South Korea, Tunisia, New Zealand, Norway, Singapore, Algyria, Slovenia, Sweden, Switzerland, United Kingdom and United States.

Table 1 gives the summary statistics for the data used in this analysis. We present three statistics which are calculated using the observations in the sample of 22 countries: Skewness, Kurtosis and Jarque-Bera. The value of Jarque-Bera test for GDP series accepts normality at 5 percent level significant. This implies that the GDP data are from a normal distribution.

4.2. Results

In this subsection, first the empirical results of the panel unit root test are presented and then if the evidence suggests that the variables do evolve as non-stationary processes, hence, it is necessary to turn to panel Cointegration techniques in order to determine whether a long-run equilibrium relationship exists among the non-stationary variables in level form. The last subsection will provide the estimation results of standard macroeconomic model and sufficiency economic model with OLS and sample selection approach.

4.3. The empirical results of the panel unit root test

Tables 2 and 3 report the panel unit root tests on the relevant variables. Most of the tests fail to reject the unit root null hypothesis for ln GDP, ln K, ln L, ln RJV and ln RD at 5 percent significance, or better, in level form are in Table 2, but the tests that reject the null of a unit root at 5 percent significance or better in difference form are in Table 3. The table 2 and 3 further report the widely used Hadri-Z test statistic, which, as opposed to the aforementioned tests, uses a null hypothesis of no unit root.

It is, therefore, necessary to turn to panel Cointegration techniques in order to determine whether a long-run equilibrium relationship exists among the non-stationary variables in the level form.

4.4. The empirical results of panel Cointegration test

This subsection applies the Koa (1999) test to test long-run relationship among economic output, macroeconomic, social and political variables are shown in Table 4.

Table 4 Kao (1999) for panel cointegration test Test Statistic

	T-Ratio	P-Value
Kao (1999) Test	-3.47***	0.00

4.5. Estimation Results

1) OLS regression without controls for selection bias.

Before starting the sample selection model, this part provides the result of the OLS regressions, without controlling for sample selection bias (see Table 5). The model after the unit root test and Cointegration test is as follows:

$$\log(gdp_{it}) = \alpha_i + \beta_1 \log(k_{it}) + \beta_2 \log(l_{it}) + \beta_3 \log(rjv_{it}) + \beta_4 \log(rd_{it}) + \beta_5 \log(fdi_{it}) + \varepsilon_{it} \quad (1)$$

These are our benchmark regressions.

The result of the Hausman (1978) test suggests that Random Effect (RE) estimation is more suitable for estimating equation (1). Therefore, equation (1) is estimated by using random effect estimation and the result is shown in Table 5.

Table 5 compares the standard macroeconomic model with the sufficiency economy inspired model on the basis of the standard error of regression, adjusted R-Squared, and the Durbin-Watson (DW) statistic for autocorrelation. The standard error of regression in the Sufficiency Economy Inspired Model is smaller, signaling less spread of estimated values around the true values. An increase in the adjusted R-Squared can be noted despite the inclusion of more variables in the model. The result indicates that the sufficiency economy is suitable to construct the economic output model for the countries.

The results in Table 5 in column 2 or the sufficiency economy inspired model indicate that money supply, trade openness, school enrollment, transparency tourism expenditure and labour supply have a significantly positive impact on economic output , while a lack of freedom has a negative impact on economic output in a developed country. Comparing coefficients, the result shows that tourism expenditure has a greater impact on economic output than the RD, the rjv, the labour and the fdi,. Increasing 1 percent of gdp will lead to increase in economic output about 0.634 percent, at the 1 percent level of significance.

2) Sample Selection Model with Copula Approach

In this section, we fit the Gaussian and Archimedean copulas, to model the economic output and selection equation.

To test whether there exists sample selection bias, we use the unbalanced panel data from 22 countries in the analysis.

We employ the sample selection with the bivariate normal assumption of the joint distribution and the five families of copula are estimated using ML estimation, the results are presented in Table 6. From the fitted normal marginals, we first need to check whether the margin of GDP has the uniform distribution by using the KS test. The result shows that the KS statistic is 0.0121 (p-value=0.3232) which accepts the null hypothesis implied that the margin of GDP is uniform, then we generate pseudo samples in the unit interval of [0,1].

From Table 6, first, this study consider the correlation coefficient or θ in all specification. The coefficient of θ is the relationship between the error term of the selection equation and the outcome equation. The result shows that θ are significantly different from zero which implied there is significantly relation between error term of the developed equation and the economic output equation or a selectively bias exists, and therefore coefficient from the OLS regression or Table 5 will features the potential source of a sample selection bias.

For the bivariate normality model (BVN) in column 1 of Table 6, the two equations (economic output equation and selection equation) show the coefficient of θ is significant indicating that selectivity bias is present under this specification.

Moreover, compare the likelihood, AIC and SIC among the bivariate normality model and models that used Archimedean copulas which are shown in columns (2)-(6). The result shows the AMH model performs the worst for these data, because of maximize the likelihood and the lowest value of AIC and SIC. Moreover, Parameter estimates do not change dramatically across copulas and the coefficients are closely related to the benchmark model (BVN).

The interpretation of the AMH model is as follows. First we interest in the coefficient of θ, the result shows that θ is significantly different from zero which implied there a selectively bias exists, and therefore coefficient from the OLS regression will be biased and inconsistent. The Kendall'tau has the same sign as the linear correlations. The linear correlation (θ) is 0.546 and Kendall'tau is 0.135. The Kendall'tau take positive value indicates the ranks of error terms in both the selection and outcome equation increase together.

Finally, this study interprets the results from the economic output equation (Table 6). The statistically significant coefficients support the idea that the macroeconomic indicators have significant effect a determining economic output.

5. Conclusion

This paper aims to search for the factors that can determine economic output in 22 countries for the period 2001-2014. Moreover, we apply the copula approach to construct a sample selection model which panel data. In general the assumption of dependence between the joint distribution of the error in the selection equation and outcome equation are bivariate normal. However, this assumption is excessively restrictive. Therefore, the copula approach is used in the specification the joint distribution which is non-normal. This involves specifying distributions for each of the margins, as well as selecting a copula function. Our discussion focuses on Archimedean copulas because of the ease of implication and the fact that it can handle high dimensional distributions.

With this sample selectivity model in hand, we first produce the OLS results then estimated the economic output equations using the sample selection approach. Our result confirms that there exists selection bias in our model which could lead to significant changes in the results of economic output analysis if we interest only the OLS results. Then, we provide sample selection approach with several specification of the joint distribution and the models are estimated by Maximum Likelihood approach. On the basis of two information criteria based on log likelihoods, it is conclude that the best fitting model is an AMH copula for the economic output model.

Table 1. Descriptive Statistics

	Obs	Mean	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Prob
GDP	286	983.086	14,369.080	3.635	2,424.344	0.111	2.876	0.772	0.680
FDI	286	5.293	36.615	10.140	6.329	-0.815	5.253	92.156	0.000
RJV	286	23.810	55.699	5.198	8.049	-0.369	4.140	21.996	0.000
R&D	286	108.268	438.092	18.969	86.893	0.240	3.603	7.067	0.029
L	286	1.039	1.648	0.644	0.156	-0.067	4.836	40.395	0.000
K	286	5.293	36.615	-10.140	6.329	-0.815	5.253	92.156	0.000

[a]The reaction was conducted in anoxic conditions.

Table 2. Results of Panel Unit root test base on 6 method test for all variables at level

	Null Hypothesis: Unit root (assumes common unit root process) Mean		Null Hypothesis: Unit root (assumes individual unit root process)			Null Hypothesis: Stationary
	Levin,Lin and Chu	Breitung	Im,Pesaran and Shin	Fisher-ADF	Fisher-PP	Hadri
logFDI	-5.055 (0.000)	3.096 (0.999)	0.320 (0.626)	5.094 (0.426)	3.807 (0.148)	6.709 (0.000)
logRJV	-1.306 (0.096)	0.103 (0.541)	0.204 (0.581)	4.814 (0.566)	3.958 (0.687)	7.565 (0.000)
logR&D	-3.276 (0.001)	0.0326 (0.513)	-0.838 (0.201)	5.673 (0.129)	4.527 (0.408)	5.897 (0.000)
logL	-4.619 (0.000)	5.410 (1.000)	0.496 (0.690)	3.078 (0.600)	4.955 (0.244)	8.456 (0.000)
logK	-3.234 (0.000)	0.629 (0.735)	0.503 (0.692)	6.803 (0.022)	6.272 (0.017)	9.174 (0.000)
logGDP	-5.838 (0.000)	1.103 (0.864)	-3.089 (0.001)	8.289 (0.001)	4.025 (0.471)	7.326 (0.000)

Note: An intercept and trend are included in the test equation. P-values are provided in parentheses. The lag length was selected by using the Akaike Information Criteria. N/A = inefficient observation.

Table 5. OLS regression without controls for selection bias Variable

	Standard Model
Constant	-4.467
ln GDP	0.070*** (3.796)
ln K	0.164*** (2.942)
ln L	0.001 (-0.023)
ln RJV	0.082* (2.752)
ln FDI	0.448*** (13.403)
ln RD	0.680*** (2.441)
D.W stat	1.408
F-Stat (Prob)	6.503 (0.000)

Note: The dependent variable is GDP. The t-statistic is in the parenthesis. A "*" indicate significance at 10 percent level, a "**" indicate significance at 5 percent level, and a "***" indicate significance at 1 percent level. The Hausman Test statistic (Prob) = 2.91 (0.89), indicate that the random effect model is appropriate.

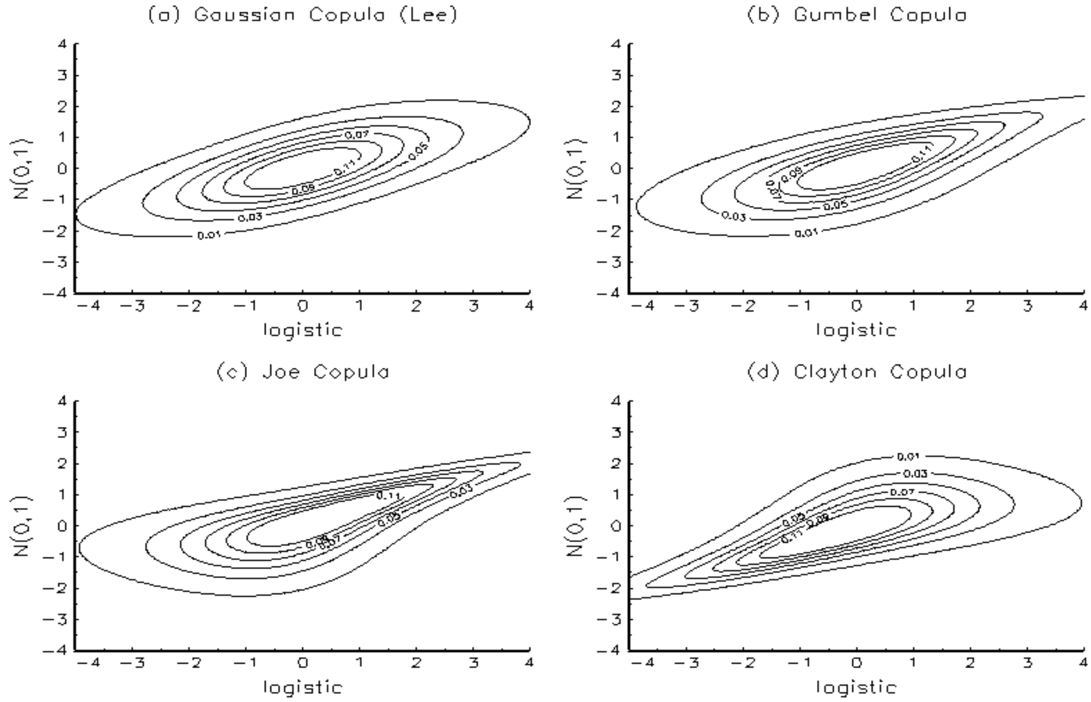
Table 6: Estimates of BVN and Archimedean Families of Copula

Varibles	BVN		Clayton		Gumbel	
	Coef	**SE**	**Coef**	**Coef**	**Coef**	**SE**
logFDI	0.120	(0.028)	0.097	(0.012)	0.187	(0.045)
		0.000		0.000		0.000
logRJV	0.090	(0.074)	0.018	(0.04)	0.113	(0.109)
		0.223		0.653		0.301
logR&D	0.100	(0.077)	0.078	(0.03)	0.232	(0.112)
		0.181		0.009		0.039
logL	0.150	(0.010)	0.086	(0.012)	0.289	(0.018)
		0.000		0.000		0.000
logK	0.810	(0.253)	1		1.394	(0.389)
		0.001				0.000
logGDP	-0.120	(0.031)	0.145	(0.003)	0.206	(0.048)
		0.000		0.000		0.000
σ	0.658	0.652	0.639	0.367	0.364	0.356
	(0.012)	(0.012)	(0.010)	(0.007)	(0.008)	(0.006)
θ	3.203	1.455	1.954	0.337	0.115	1.760
	(0.727)	(0.130)	(0.308)	(0.078)	(0.109)	(0.193)
$K\tau$	0.325	0.313	0.345	0.219	0.054	0.297
$S\rho$	0.473	0.449	0.491	0.323	0.081	0.428

Table 6: Cont

Varibles	AMH		FRANK		JOE	
	Coef	**SE**	**Coef**	**Coef**	**Coef**	**SE**
logFDI	0.679	0.698	0.695	1.213	1.194	1.156
	(0.201)	(0.204)	(0.205)	(0.355)	(0.353)	(0.361)
logRJV	0.348	0.357	0.358	0.629	0.595	0.637
	(0.035)	(0.035)	(0.035)	(0.064)	(0.066)	(0.063)
logR&D	0.590	0.606	0.597	1.086	1.106	1.049
	(0.106)	(0.106)	(0.105)	(0.182)	(0.183)	(0.179)
logL	0.202	0.201	0.201	0.345	0.341	0.354
	(0.039)	(0.039)	(0.040)	(0.070)	(0.069)	(0.071)
logK	0.577	0.580	0.583	1.227	1.208	1.231
	(0.945)	(0.094)	(0.093)	(0.209)	(0.207)	(0.207)
logGDP	0.132	0.135	0.133	0.237	0.231	0.240
	(0.021)	(0.021)	(0.021)	(0.037)	(0.037)	(0.037)

Figure 1. Plots of Gaussian, Gumbel, Joe and Clayton Copulas: Normal and Logistic marginals



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