Determining the Nature of Dependency between Agribusiness and Non-Agribusiness Stocks

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Abstract

During the financial downturn of 2008, asset classes that investors traditionally found to have low correlation with U.S. stocks became more highly correlated at the most inopportune time. Post-downturn, investors increasingly looked for alternative assets that offer diversification benefits, one of which being farmland. One of the challenges of investing in farmland is that the asset is not a securitized, low-cost investment. The current research investigates the whether exposure to farmland via an index of agribusiness stocks provides significant diversification benefits. We estimated the dependence between daily returns of the S&P 500 and an index of agribusiness stocks from 1970 through 2008 using copulas. We find significant evidence that agribusiness stocks have strong lower tail dependence with large U.S. stocks and are actually less correlated in the upper tail of the distribution. Meaning, the agribusiness index moves in near lockstep with U.S. stocks in downturns and more independently in large upswings. This provides little evidence to support the investment strategy of purchasing agribusiness stocks broadly to gain exposure to farmland.

Keywords: Agribusiness Stocks, Copulas, Risk

JEL codes: G10, G11, Q13, Q14

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Introduction

The goal of a prudent investor is to maximize risk-adjusted returns. A cornerstone of this approach is properly diversifying investments to minimize non-systemic risk (firm specific risk). Investment managers around the globe look to execute this strategy for their clients daily. As an investment manager in 2007, I set out to employ this same strategy for the clients with which I worked[1]. A peculiar and now well-documented phenomenon was emerging, asset classes that had once demonstrated relatively low correlation with U.S. stocks now had significantly increased.

An article in Forbes by William J. Coaker, Jr. describes this situation, “Investors who increased allocations to international stocks, emerging markets, real estate, hedge funds, high-yield bonds, and natural resources during the previous decade did so at least in part because these investments’ correlations to U.S. stocks, and to each other, had been low in the pasted” (MacBride 2011). As correlations rose in 2008-2009, “the expected reduction in risk did not occur, and in the 2008 bear market investors suffered much larger losses than expected.” Table 1 shows how the correlations calculated by Coaker help illustrate the relationships between the aforementioned asset classes and the S&P 500.

	Emerging Markets	High-Yield Bonds	U.S. Bonds	Global Bonds	U.S. Treasuries	Real Estate	Natural Resources
1970/Inception—1999	0.51	0.51	0.28	-0.06	-0.02	0.58	-0.02
2000-2004	0.77	0.47	-0.29	0.03	-0.15	0.27	-0.05
Jan 2005-Oct 2007	0.60	0.70	-0.10	-0.10	0.15	0.61	-0.10
Nov 2007-Dec 2009	0.87	0.79	0.31	0.29	-0.14	0.83	0.55
2005-2009	0.82	0.76	0.21	0.19	0.12	0.81	0.41

Table 1: Correlation between S&P 500 and seven asset classes (MacBride 2011)

[1] From 2005 to 2008, Jeremy M. D’Antoni was employed as an investment manager.

Since 2008, one asset class that has become of great interest to investors both inside and outside of agriculture is farmland. Billions of dollars have flowed into farmland investment funds at MetLife, Manulife Financial, and other institutional investment managers. Manulife Financial's agricultural investment manager, Hancock Agricultural Investment Group, describes their reasoning for the potential diversification benefits of farmland in the following manner, "Historically, farmland returns have been negatively correlated with stocks and bonds and have exhibited only a modest positive correlation with commercial real estate. These characteristics make it an excellent diversification toll than can help reduce the impact of broader market volatility on a diversified portfolio" (HAIG 2012). These attributes made farmland an attractive vehicle for those investors that found little success by diversifying their portfolio via many of the asset classes listed by Coaker.

The problem for most individual investors is simply that they cannot meet the high investment minimums required to invest in farmland through institutional funds. Similarly, investors who are used to the liquidity that the market offers are likely to have little interest in sacrificing this liquidity by investing directly in farmland. A potential and unexplored alternative could be in accessing investment in the underlying farmland by buying securities with direct exposure to farmland. Individuals desiring exposure to gold often employ a similar strategy; whereby, investors purchase the stock of a gold mining company rather than purchasing the commodity itself.

The work of Clark et al. (2012) developed a value-weighted index of agribusiness stocks. A potential strategy for investors could combine the strategies of indirect exposure to farmland with the low-cost investment strategy of passive investing or indexing. Such a security could be cheaply offered to investors in the form of a mutual fund or ETF and potentially offer significant diversification benefits at a lower initial investment cost relative to either direct investment in farmland and/or through investment in intuitional funds.

The purpose of this research is to determine how an index of agribusiness stocks performs relative to the S&P 500. The particular area of interest of our research is how the agribusiness index performs in the left tail of the return distribution (the bear market). We want to determine whether this asset class, agribusiness stocks, also experiences an increase in correlations in periods of significant U.S. stock market declines. As common in modeling asset allocation, risk modeling, and other financial relationships, we use copulas to determine the dependency between the S&P 500 and agribusiness stock index (Bouye et al 2000; Embrechts et al 2003, Cherubini et al 2004, Patton 2006, and Zimmer 2012). Linear correlation assumes a bivariate normal joint distribution function between returns, but copulas allow us to relax this assumption. We can specify the marginal distribution of returns for the S&P 500 and agribusiness index independently. Further, the copula function that ties these marginal distributions together and "synthetically" creates a joint distribution function is specified independently of our distributional choices for the marginal distributions.

Interestingly, copulas themselves have been blamed as a cause of the stock market declines of 2008. A 2009 article in Slate magazine title, "Recipe for Disaster: The Formula that Killed Wall Street" describes the use or rather misuse of the Gaussian copula as a significant cause of financial collapse (Salmon 2009). The Gaussian functional form is asymptotically independent in the tail regions; therefore, financial assets are deemed uncorrelated by this model in left-tail market events. Subsequent research, since 2009 has generated alternative functional forms for copulas that are superior to the Gaussian when modeling financial assets (Zimmer 2012).

Following the recommendations of Zimmer (2012), we estimate models using the Clayton, Gumbel, Clayton-Gumbel mixture, and Gaussian Copulas. Using nonlinear optimization, we estimate the dependency between daily returns for the S&P 500 and the agribusiness stock index from 1970 through 2008. Our results indicate that the correlation between these indexes is extremely high and greater than what is implied when using linear correlation measures. Moreover, the correlation remains near perfectly positive in the lower tail region but declines significantly in the upper tail region of the distribution. This implies that extreme declines in value of U.S. stocks will be near perfectly matched by the agribusiness stock index; yet extreme increases in value will not be completely shared. This relationship does not seem to mimic that of farmland relative to U.S. stocks.

Literature Review

Agribusiness indexes have only recently been available to investors. The first such index is the Standard & Poor's Global Agribusiness Index. The index began trading on May 19, 2008 and includes 24 of the largest publicly traded agribusiness stocks operating in the following sectors agricultural products, fertilizers and agricultural chemicals, construction/farm machinery/heavy trucks, and packaged foods and meats. Given its limited breadth, this index neglects many significant sectors of the agricultural sector necessary to provide a more complete view of the agrifood system. Clark et al. (2012) created an agribusiness index that includes such industries as farm production, agricultural input industries, agricultural services, forestry, fishing, agricultural processing and marketing industries, wholesale and retail trade of agricultural products, and indirect agribusinesses, too deal with these omitted sectors.

For the purposes of this research, this distinction is very important. We are investigating whether the performance of an agribusiness index can proxies the relationship between farmland

and U.S. Stocks. The index created by Clark et al. (2012) includes industries like farm production with more direct exposure to land prices; therefore, it provides the preferable index to investigate the dependency relationship. In the research by Clark et al. (2012), the linear correlation between the agribusiness index and the S&P 500 from 1970 to 2008 was 0.7376. From 1999 to 2008, the correlation measure was lower at 0.5583. In the most recent period from 2004 to 2008, the correlation was much higher at 0.9692.

While these correlation figures provided questionable evidence of the diversification benefit of the index, the beta values provided evidence that is much more favorable. Using five-year averages, the beta values for the agribusiness index can be found in table 2. In the three most recent periods, the beta value is considerably lower than one, thereby indicating that agribusiness securities are more defensive that the market. Further, the results of Sharpe ratio tests indicated that the risk-adjusted returns of the index were greater than comparable indexes in nearly half of the 39 years studied.

Return Periods	**AGB Index Beta Estimation**
1970-1974	0.9770
1975-1979	0.9257
1980-1984	0.9221
1985-1989	1.1223
1990-1994	1.1313
1995-1999	0.8328
2000-2004	0.3986
2005-2008	0.7644

Table 2: Five-year Average Beta Estimation

Such evidence motivated the current research to determine just how defensive and robust agribusiness stocks can be expected to be in market downturns. The methods used to evaluate this proposition are copulas. The use of the copula methodology in economic time series has been well documented (Trivedi and Zimmer 2007; Patton 2012). The popular press has also paid great attention to the use of the Gaussian copula; first in *The Black Swan* a book by Nassim Taleb (2007) and then in articles found in Wired (Salmon 2009), The Economist (2009), Financial Times (Pollack 2012), and Reuters (Salmon 2012). Most of these articles center on the use and misuse of the Gaussian copula by financial firms prior to the financial downturn and some criticize those that popularized the use of the model. David Li (2000) introduced the Gaussian copula for applications in fixed income; however, it should be noted that he mentions that mixtures of copulas could yield improved results.

Zimmer (2009) provides a thorough evaluation of the proposition Li (2000) that mixtures of copulas may yield superior fits to the Gaussian copula. He specifically addresses this comparison in the context of the housing crisis using the Gaussian, Gumbel, Clayton, and Clayton-Gumbel mixture copulas. Using six state pairs, the goal of his research was to determine whether falling housing prices in one state impacted housing prices in another.

Zimmer (2009) reports Bayes Information Criteria (BIC) estimates for each copula specifications across the six state pairs. The Gaussian copula had neither the lowest BIC nor best fit for any state pairing. Hypothesis testing further showed that for all but one state pair, the mixture model had a significantly better fit than the Gaussian at the .05 level. For the one state pair that was insignificant with respect to the mixture model fit being better than the Gaussian, the Gumbel copula demonstrated a statistically significant improvement in fit over the Gaussian copula. These results provided an excellent framework on which we built our analysis. Like Zimmer (2009), the current research utilizes the Gaussian, Gumbel, Clayton, and Clayton-Gumbel specifications and reports BIC values for each model.

Methods

An *m*-dimensional copula (*C*) connects an *m*-dimensional cumulative distribution function (*F*) to the one-dimensional marginals ($F_1, \ldots, F_m$) such that:

$$F(y_1, \ldots, y_m) = C(F_1(y_1), \ldots, F_m(y_m)) \quad (1)$$

where *y* represents the variables of interest. Specifically, a two dimensional copula using returns of the S&P 500 (y_1) and agribusiness index (y_2) is presented as:

$$F(y_1, y_2) = C(F_1(y_1), F_2(y_2);\ \theta) \quad (2)$$

and includes a dependence parameter (θ). This parameter measures the dependence between the marginal distributions. If θ=0, then the marginal distributions are statistically independent. If θ is significantly different than zero, then this parameter estimate can be used to calculate a correlation measure between the indexes. Both copula functions and the respective marginal distributions are fit to the data via maximum likelihood estimation. An important advantage of copulas in this regard is flexibility in distributional assumptions. The marginal distributions can be chosen independently of each other. Additionally, the copula function can be chosen independently of the marginal distributions.

Gaussian Copula

The Gaussian copula is a symmetric function allowing both positive and negative dependence and had the following functional form:

$$C_{Gauss}(u_1, u_2,;\ \theta) = \ \Phi_G(\Phi^{-1}(u_1), \Phi^{-1}(u_2); \theta) \quad (3)$$

$$= \int_{-\infty}^{\Phi^{-1}(u_1)} \int_{-\infty}^{\Phi^{-1}(u_2)} \frac{1}{2\pi(1-\theta^2)^{1/2}}\ x \left\{\frac{-(s^2 - 2\theta st + t^2)}{2(1-\theta^2)}\right\} dsdt$$

The marginal distributions are represented by u_1 and u_2 in equation (3). The domain of the dependence parameter θ is $(-1 < \theta < 1)$. In equation 3, Φ represents the standard normal cumulative density function (CDF) and $\Phi_G(.,.)$ represents the standard bivariate normal distribution. The primary weakness of this specification is that asymptotic independence is imposed in the tail regions; therefore, measures of lower and upper tail dependence cannot be calculated. To permit comparison across copula functions and aid in greater interpretability of results, a Kendall rank correlation coefficient (Kendall's τ as it is commonly called), measure of correlation is calculated (Huard et al. 2006; Kendall 1938).

$$\rho_{Gauss} = \frac{2}{\pi}\arcsin(\hat{\theta}) \tag{4}$$

Clayton Copula

The Clayton copula is not symmetric and limited to only positive dependence. The domain of the dependence parameter θ is $(0 < \theta < \infty)$. At the zero lower bound, the marginal distributions are independent. The Clayton copula is defined:

$$C_{Clay}(u_1, u_2,;\ \theta) = \ (u_1^{-\theta} + u_2^{-\theta} - 1)^{-1/\theta} \tag{5}$$

and our results for the dependence parameter (θ) are reported using the the Kendall's tau (ρ_C) where:

$$\rho_{Clay} = \ \frac{\theta}{\theta+2}\,. \tag{6}$$

While the Clayton copula does not permit negative dependence, the Clayton copula exhibits greater levels of dependence in the lower tail of the distribution than the upper tail. A measure of lower tail dependence is calculated:

$$\rho_{Lower} = 2^{-\frac{1}{\theta}} \tag{7}$$

Gumbel Copula

Similar to the Clayton copula, the Gumbel is an asymmetric function and does not permit negative dependence. The domain of the dependence parameter θ is $(1 \leq \theta < \infty)$ and functional form for the Gumbel copula is

$$C_{Gumb}(u_1, u_2,; \theta) = \exp(-(\bar{u}_1^{\theta} + \bar{u}_2^{\theta})^{\frac{1}{\theta}}) \qquad where\ \bar{u}_j = -\log(u_j) \tag{8}$$

Results for the dependence parameter (θ) are reported using Kendall's tau (ρ_{Gumb}) where

$$\rho_{Gumb} = 1 - \frac{1}{\theta} \tag{9}$$

What separates the Gumbel copula from the Clayton is that dependence is stronger in the upper tail of the distribution than the lower. This upper tail dependence is calculated:

$$\rho_{Upper} = 2 - 2^{\frac{1}{\theta}}. \tag{10}$$

Clayton-Gumbel Mixture

The mixture of the Clayton and Gumbel copulas is done using the following function

$$C_{Mix}(.) = \pi\, C_{Clay}(.) + (1 - \pi)\, C_{Gumb}(.) \tag{11}$$

where π is an estimable parameter restricted to the interval (0,1) that measures the proportion of the model attributable to the Clayton function. This mixture model provides a copula that measures both upper and lower tail dependence. The domain of the dependence parameter for the Clayton portion maintains all the properties of that functional form and likewise for the Gumbel portion.

Visual Comparison of Copulas

Zimmer (2009) provides scatter plots (Figure 1) of simulated data from each copula in his research, which helps the reader visualize the difference in characteristics of the functional forms. The data generated is 2,000 observations with a magnitude of dependence of 0.60 and standard normal marginal distributions. From these plots, the behavior of each function in the tail regions becomes clear. The Gaussian exhibits independence in the extreme tail regions. The Clayton copula shows far greater dependence in the lower tail of the distribution while the Gumbel displays much greater dependence in the upper tail. The mixture model has a more symmetric shape, similar to the Gaussian, but the greater tapering of the distribution in the tails displays the properties of tail dependence associated with the respective Clayton and Gumbel functions.

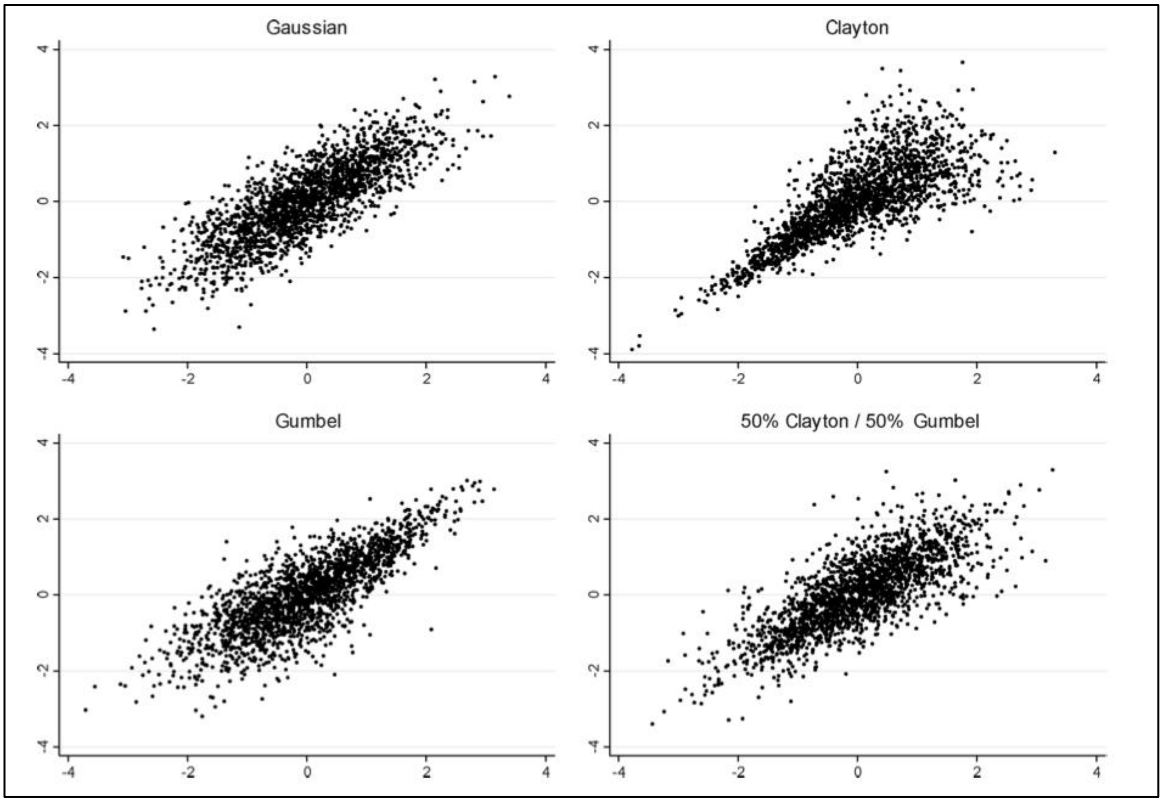

Figure 1: 2000 Simulated Values for Alternative Copula Distributions (Zimmer 2009)

Estimation

The estimating function used Zimmer (2009) and employed in this research is shown below:

$$F(\hat{y}_{1,t}, \hat{y}_{2,t}) = C(F_1(\tilde{y}_{1,t}), F_2(\tilde{y}_{2,t});\ \theta) \tag{12}$$

when the marginal distributions are substituted into the copula function. This can then be restated in probability density function (PDF) format:

$$c(F_1(\tilde{y}_{1,t}), F_2(\tilde{y}_{2,t}); \theta) = \frac{\partial C}{\partial F_1 \partial F_2}\ f_1 x f_2 \tag{13}$$

where $f_1$and f_2 are PDF's. After taking the natural log of equation 13 and summing across all observations, the function can be maximized with respect to θ to estimate parameters via maximum likelihood. Estimates are generated for each of our four copula models and all dependence parameters are reported in terms of Kendall's τ. The Bayes Information Criteria (BIC) is also reported for each estimation where:

$$BIC = -2\ln(L) + kln(n) \tag{14}$$

where $\ln(L)$ is the log likelihood from the estimation, k is the number of estimated parameters, and n is the number of observations. This measure of goodness of the fit for our models implies better fit as BIC decreases.

Data

The agribusiness stock index data used in this research was created by Clark et al. (2012). This research outlines the creation of an agribusiness stock index using information obtained from the Center for Research in Security Prices Database (CRSP) accessed through Wharton Research Data Services (WRDS). The CRSP database is the leading provider of the most comprehensive U.S. historical stock market databases (New York Stock Exchange (NYSE), American Stock Exchanges (AMEX) and National Association of Securities Dealers Automated Quotation System (NASDAQ)). This database contains daily stock prices for agribusiness corporations and daily data for the S&P 500.

Both the agribusiness stock index and S&P 500 are market-capitalization-weighted indexes—meaning corporations with the largest market capitalizations are weighted the greatest in the index. For the S&P 500, this index includes the 500 largest corporations across all sectors of the equity market. Agribusiness stocks are defined according to the Economic Research Service's (ERS) definition of an agribusiness (Economic Research Service, 2005). These ERS classifications are matched to corresponding U.S. Economic Census Standard Industrial Classification Codes (SIC codes) of firms related to agriculture (U.S. Census Bureau, 2009).

This provided an initial list of 374 corporations classified as farming, closely related to farming, or peripherally related to farming. From these companies, an index comparable to the S&P 500 was created for the years 1970 through 2008. Figure 2 illustrates the relative performance of these indexes over the 39-year period. The divergence between the indexes is relatively gradual through the mid-1980's and then rapidly departs over the following two decades. By 2008, the value of the S&P 500 was approximately 10 times greater than the agribusiness index. To avoid problems associated with different scales and to address the issue of dependency from a more meaningful perspective for investors, the index values were translated into daily returns. The daily return data used in this research is calculated for an average of approximately 252 trading days per year from 1970 to 2008. This yields 9,844 observations for the daily returns of the agribusiness stock index and S&P 500.

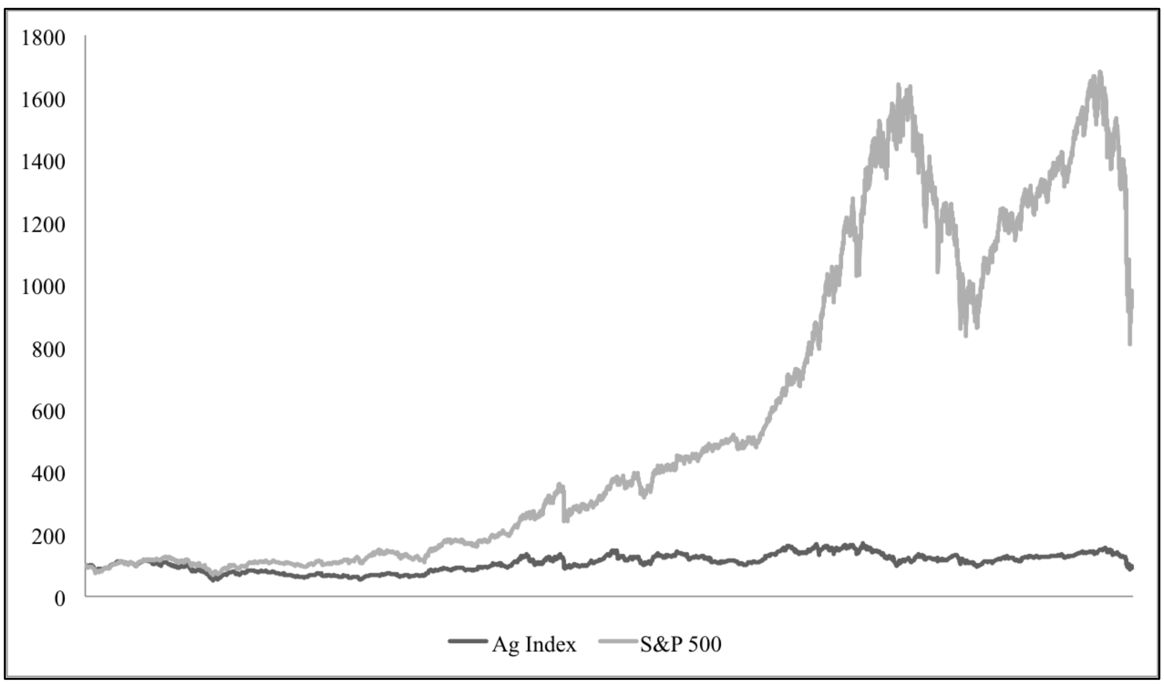

Figure 2: Comparison of the Ag Index Value to the Value S&P 500(Clark et al. 2012)

Results

Table 3 contains the estimation results and goodness of fit measures for each of the four copula function specifications. The estimated dependence parameter for each copula model is reported in terms of its Kendall's τ to facilitate comparison across models. Goodness of fit for each of the models increases as the Bayes Information Criteria (BIC) decreases.

Copula	**Estimates**
Gaussian	
$\hat{\tau}$	0.9555***
Bayes Information Criteria (BIC) Value	108,988.246
Clayton	
$\hat{\tau}$	0.9955***
Lower-tail Dependence	0.9984
Bayes Information Criteria (BIC) Value	-56,872.94
Gumbel	
$\hat{\tau}$	0.9989***
Upper-tail Dependence	0.9993
Bayes Information Criteria (BIC) Value	-93,168.61
Clayton-Gumbel Mixture	
Clayton $\hat{\tau}$	0.9953***
Gumbel $\hat{\tau}$	0.4723***
Lower-tail Dependence (Clayton)	0.9983
Upper-tail Dependence (Gumbel)	0.5584
Proportion due to Clayton ($\hat{\pi}$)	0.9944
Bayes Information Criteria (BIC) Value	-57,485.64

Table 3: Copula Estimation Results

The BIC shows that the best-fit model was the Gumbel copula with the worst fit being the Gaussian. The Clayton and Clayton-Gumbel mixture models fell between the extremes in terms of fit and were very close with BIC's of -56,872.94 and – 57,485.64, respectively.[2] This is to be expected since the portion of the Clayton-Gumbel mixture model attributable to the Clayton copula is .9944, i.e. virtually all dependence captured by mixture model is attributable to the Clayton copula. This result implies that lower tail dependence is more prevalent than upper tail

[2] It should be noted that the goodness of fit for the Clayton-Gumbel is penalized for the greater number of estimated parameters under the BIC measure.

dependence in the mixture model. In terms of the goals for this research, this mixture model illustrates that dependency between returns of agribusiness stocks and S&P 500 is stronger in the lower tail of the distribution than the upper tail. This does not bode well for the prospects of agribusinesses stocks acting as a safe-haven during large negative market shocks like the 2008 financial collapse, and is in contradiction with the research of Damodran (2009) who suggests that agribusiness stocks are defensive in nature.

For measures of dependency, we report correlation measures separately for the Clayton and Gumbel portions of the two-component mixture model. All dependency parameters on which these correlations measures are based were significant at 99% confidence. The Clayton portion estimates that the correlation between the returns of the agribusiness index and the S&P 500 is 0.9953 with lower tail dependence of 0.9983. The single-component Clayton model provided estimates of the correlation between returns at 0.9955 and lower-tail dependence at 0.9984. The Gumbel portion of the two-component mixture model shows a correlation between the indexes as 0.4723 with upper tail dependence of 0.5584. The single-component Gumbel model provides estimates of correlation between returns at 0.9989 and upper tail dependence at 0.9993. Since the Gaussian copula is asymptotically independent in the upper and lower tails, dependence of returns must be tested while neglecting both tail regions. The results show a correlation measure of 0.9555, which is significant at the 1 percent level and nearly identical to the other three copula specifications. Notice also the considerable change in results for the Gumbel specification between the single and mixed copula models.

It is worth noting that the Clayton specification remained relatively unchanged between the single and mixed copula models. These results indicate that there is valuable information that can be found in both tails of the distribution. If we utilize only the single-component copulas, we ignore this information, and may in fact make incorrect investment decisions, i.e. that agribusiness stocks always move with the market, which this research shows not to hold true especially for a bull market.

Conclusions

This research investigated whether the performance of a comprehensive agribusiness stock index (Clark et al. 2012) can proxy the relationship between farmland and U.S. Stocks, i.e. that agribusiness stocks are defensive nature. To test this relationship we examined four copulas (the Clayton, Gumbel, Clayton-Gumbel mixture, and Gaussian Copulas) via nonlinear optimization, we estimated the dependency between daily returns for the S&P 500 and the agribusiness stock index from 1970 through 2008. The results indicate that the correlation between these indexes is extremely high and greater than what is implied when using linear correlation measures (Clark et al. 2012). Perhaps the most import result comes from the Clayton-Gumbel mixture cupola, which shows during market downturns the agribusiness stock index and the S&P 500 move together, but for upturns in the market the agribusiness index is not able to generate as high of a return as the S&P 500. This result provides indication that the agribusiness index is not a good investment proxy for farmland.

For future research would seek to examine the relationship between the S&P 500 and the many commodity price indexes now available for public investment; commodities are an asset class that might be even more closely related to farmland values than a mutual fund of agribusiness stock. The rise of commodity index funds (Dow Jones-UBS Commodity Index (DJUBSCI), the Rogers International Commodity Index (RICI), the S&P Goldman Sachs Commodity Index (S&PGSCI), and the Thomson Reuters/Jefferies CRB Index (TRJCRB)) available for public investments indicates that large investment firms have seen a demand for these instruments. If commodity indexes are defensive in nature, much like farmland, they could play a valuable role in the portfolio of many investors. We would also like to further research the subsets of the agribusiness index with the closest proximity to agricultural production to determine whether they provide a proxy for farmland values.

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