Price Dependencies of Margin Coverage

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Introduction

The agricultural sector has been experiencing different types of risk and different remedies for those risk factors. Modeling dependence structures among risk factors, such as output prices and yields, has played an important role in agricultural insurance. Nowadays, investigation of output and input price relation in Margin Coverage (Protection) concept and risk factors raised from this relation is getting more popular.

Objectives

- The objective of this study is to investigate the dependence structure between inputs — fertilizers — and output prices of corn and soybean motivated by Margin Coverage.
- We use combinations of pair-wise copulas — Vine copulas — to model multiple sources of risk such as fertilizer prices and output prices of corn and soybean.
- With this study, we aim to provide better insights for the rapidly developing market for risk management mechanisms that address a broad set of dependent risks.

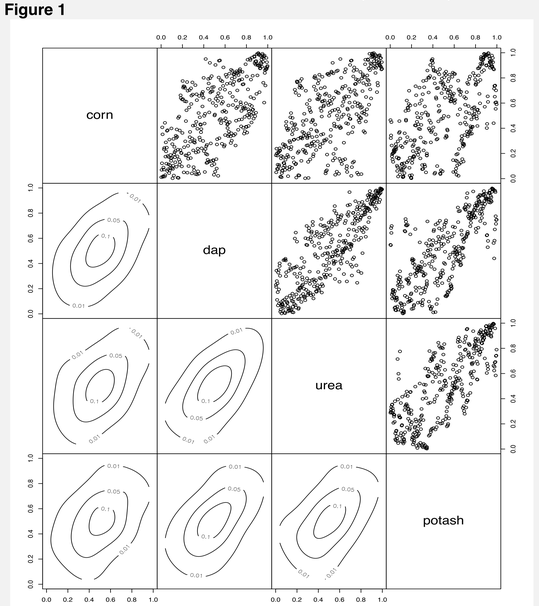
Data and Methods

- In agricultural economics, copula-based methods are of great importance in many areas, including the rating of insurance for agricultural production as well as in agricultural policy analysis contexts
- Copula models use a function called “copula” to tie together two or more marginal probability functions which may or may not be related to one another to form a joint probability distribution function. $F(x_1, x_2, \ldots, x_p) = F(F_1^{-1}(u_1), F_2^{-1}(u_2), \ldots, F_p^{-1}(u_p)) = C(u_1, u_2, \ldots, u_p)$
  The density function of the copula, *c*, then can be written as:
  $c(u_1, u_2, \ldots u_p) = f(F_1^{-1}(u_1), \ldots, F_p^{-1}(u_p)) / \prod_{i=1}^{p} f_i(F_i^{-1}(u_i))$
- For the underlying purpose of this study, we use monthly sale prices of urea, potash, DAP (Diammonium Phosphate price) for corn; DAP and potash for soybean. The data cover 30 years period spanning 1987-2017.
- In this research, margin difference between fertilizers and output price is explained and visualized with *canonical vine* (C-Vine) copula to overcome the challenge of higher order dimensions.
- Bedford and Cooke (2002) and Kurowicka and Cooke (2006) show how multivariate data can be modeled using pair copulas. Aas et al. (2009) demonstrate that multivariate density can be expressed as a product of pair-wise copulas. Following Ass et al. (2009), a joint multivariate density function for n variables can be written as:
  $f(x_1, x_2, \ldots\ldots, x_n) = f_n(x_n).f(x_{n-1}|x_n).f(x_{n-2}|x_{n-1}) \ldots f(x_1|x_2 \ldots x_n)$
  and $f(x_{n-1}|x_n)$ can be written as:
  $f(x_1|x_2, x_3) = c_{(13)|2}\{F(x_1|x_2), F(x_3|x_2)\}.f(x_1|x_2)$

Results

In Figure 1, we show the price relation between dap, urea, potash and corn with contour plots. Figure 2 shows the price relation between dap, potash and soybean. Tree 1 in Figure 1 depicts the C-Vine first tree structure of corn, dap, urea and potash. The C-Vine tree in Figure 2 shows the first tree structure of soybean, dap and potash.

Figure 1



Tree 1

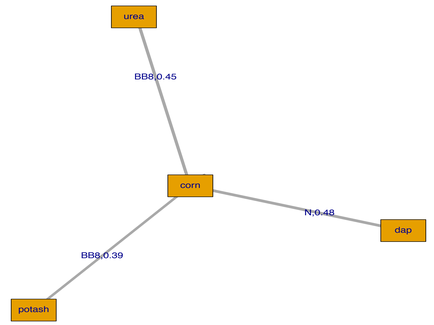
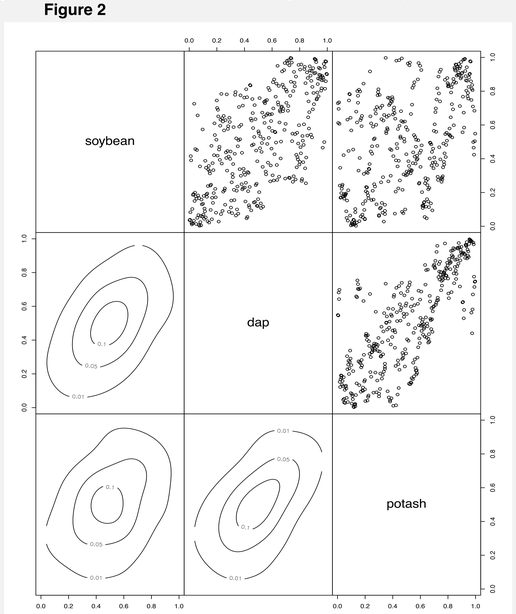
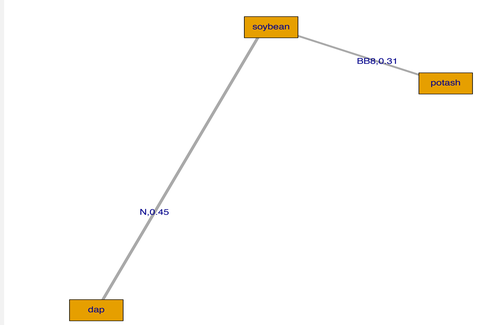


Figure 2

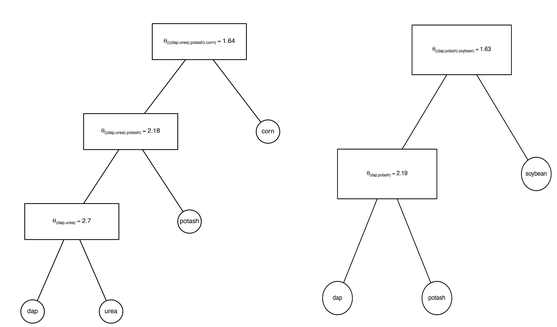


Tree 1



Results

- Contour-plot results from C-vine copula for corn and related inputs show that there is strong tail relation between dap and urea. Graphical relations tell us different types of relations between pairs. In addition to graphical analysis, we also applied independence test, based on Kendal-τ, to confirm whether the pair relations are strong or not. It confirms our graphical analysis of dependence between pairs. As model estimation step, we apply sequential MLE estimation.
- After figure out the strongest dependence, we use Vuong test to decide which copula among 20 copula families fits better for the pair copulas. In Figure 1, we find that BB6 copula fits better for dap and urea. Gaussian copula fits better for corn and dap. For the rest of the pairs in Figure 1, BB8 copula fits better.
- For soybean, dap and potash relation in Figure 2, Gaussian copula fits better for soybean and dap, and for rest of the pairs BB8 copula fits better.
- In addition to C-Vine copula, we also use the Hierarchical Archimedean copula (HAC) structure to show the dependence between prices. Higher generator functions’ ,θ’s, values show stronger tail relations.



Conclusions

- The use of copula in higher dimensions is challenging. To overcome the higher dimension challenge, we apply Vine copula methodology to present the dependence structure of corn and soybean with their fertilizer prices.
- The results demonstrate important implications for the pricing of portfolios of risks. By creating a concrete dependence structure for crop prices and input (fertilizers) prices, I aim to provide better insights for agricultural crop insurance programs.