ABSTRACT

AHMED, MD MANSUR. Essays on Non-Farm Labor Supply Effects of Farm Mechanization, Commodity Market Linkages, and Trade Effects of Exchange Rate Uncertainty. (Under the direction of Dr. Barry K. Goodwin.)

This dissertation includes three essays. The first essay investigates what role the adoption of agricultural mechanization plays in the decision to participate in off-farm activities using a longitudinal data set from Bangladesh. This paper uses an agricultural household model to establish the link between labor-saving technology adoption decisions and off-farm participation decisions. To control for potential endogeneity between these decisions, we use the bivariate probit model (BPM), the endogenous switching probit model (SPM), and the endogenous treatment effects (ETE) model. The results from the BPM and the SPM confirm that farm households with mechanized farming technology tend to participate more in the non-farm sector. The results from the ETE model also confirm that the farm households that adopt labor-saving technology supply more labor hours in the rural non-farm sector.

The second essay investigates the dependence structure among international food grain markets using nonlinear copula models. This essay examines how volatility and skewness spillovers work in international food grain markets. This essay uses the copula approach to study the comovement of prices for three most traded food grains: rice, wheat, and corn. The results suggest that the food grain markets are clustered based on geographical proximity. While there is a strong dependence on food grain markets in the Americas, the dependence between food grain markets in the Americas and the rice market in Thailand is feeble. Thus, the shocks in one region's food grain markets should not affect the food grain markets in another part of the world unless market agents panic and respond hastily. This essay also shows

that the dependence structure can be better captured through the use of non-Gaussian copulas than through the use of conventional Gaussian copula.

The third essay deals with exchange rate volatility and its impact on trade volume. This study introduces a novel and superior measure of exchange rate volatility to the literature. While the use of a backward-looking measure of exchange rate volatility based on a time series model is common in literature, this research uses a new forward-looking measure of exchange rate volatility, called here "options implied volatility," to evaluate its impact on trade flows. Using a panel fixed-effects model, the study finds that a negative exchange rate volatility has effects on trade volume only for developing countries, not for advanced economies. The results imply that traders in advanced economies can hedge the exchange rate risk through exchange rate options. The study also finds that the trade effects of exchange rate volatility vary across sectors; manufacturing, chemical & machinery trade are adversely affected by exchange rate volatilities, and the agricultural trade is found to be unresponsive to exchange rate volatilities.

Essays on Non-Farm Labor Supply Effects of Farm Mechanization, Commodity Market Linkages, and Trade Effects of Exchange Rate Uncertainty

by
Md Mansur Ahmed

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APPROVED BY:

Dr. Barry K. Goodwin Chair of Advisory Committee	Dr. Mehmet Caner
Dr. Ivan Kandilov	Dr. Sujit Ghosh

DEDICATION

To my mother, Ms. Zarina Begum.

BIOGRAPHY

Mansur Ahmed was born in Brahmanbaria, Bangladesh in 1981. He received his Bachelor of Social Science degree in Economics from the University of Dhaka, Bangladesh. He also received his Masters of Social Science degree in Economics from the same university. Mr. Ahmed received another Masters of Science (MS) in Economics degree from the North Carolina State University in 2012. After his graduation from University of Dhaka, he worked at the South Asian Network on Economic Modeling (SANEM) and the Bangladesh Institute of Development Studies (BIDS) as a Research Associate. He also served as Visiting Faculty at the ASA University of Bangladesh, Dhaka, Bangladesh. Mr. Ahmed has been working as consultant at the World Bank Headquarters in Washington DC since 2014. Earlier, he also worked at the UNDP as consultant in the summer of 2013. His research interests include agriculture and rural development, poverty and inequality, international trade and development, and applied econometrics.

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CHAPTER 1: AGRICULTURAL MECHANIZATION AND NON-FARM LABOR SUPPLY OF FARM HOUSEHOLDS

1.1. Introduction

Economic opportunities in the non-farm sector have long been recognized as an integral part of rural livelihoods in developing countries (see Lanjouw & Lanjouw, 2001; Lanjouw & Feder, 2001). The non-farm sector is an important source of employment in many countries, and it has been a key driver of overall economic development in many East Asian economies (Lin & Yao, 1999; Lanjouw & Lanjouw, 2001; McCulloch, Timmer, & Weisbrod, 2007). It is also evident that non-farm income is critical to the welfare of rural households in developing countries (Rosenzweig, 1988). In many developing countries, a considerable portion of farm households earn income from non-farm sources, and income from the non-farm sources constitutes between 20% and 70% of total household earnings (Adams, 2002; Newman & Gertler, 1994; Reardon, Taylor, Stamoulis, Lanjouw, & Balisacan, 2000; Rizov, Mathijs, & Swinnen, 2000). One need not be a skilled worker to engage in non-farm economic activities;[1] unskilled labor is the primary source of non-farm earnings for the poorest subsistent African farmers, who often earn a significant share of their income from non-farm sources (Barrett, Reardon, & Webb, 2001; Reardon, 1997).

The importance of the non-farm sector as a source of rural employment, and as a driver of rural economic growth and poverty reduction, is growing all over the developing world. For example, in Bangladesh, growth in rural non-farm income accounted for 40% of poverty

[1] The terms non-farm and off-farm are used interchangeably in this chapter to mean work in the non-farm sector.

reduction between 2000 and 2005, while growth in farm income contributed only about 21% in the same period (World Bank, 2013). In Bangladesh, the rural non-farm sector is no longer viewed as "residual" sector, and it remains a persistent employment source of half of the rural workforce since the mid-1980s (Sen, 1996; World Bank, 2016). The extremely narrow scope for expanding agricultural land, the growing educated labor force, and the increasing demand for non-farm goods and services all imply that future economic development policies in densely populated developing countries will focus on ensuring robust growth of the rural non-farm sector.

Despite the structural changes in most developing economies, the labor force has not moved out of agriculture as rapidly as expected, although successful movement of surplus labor from agriculture to the advanced sector has long been considered to be an important feature of economic development. Labor migration from the rural farm sector to the advanced urban sector has been analyzed for many countries and at many points of time (see Lewis, 1954; Harris & Todaro, 1970). However, extraordinary agricultural growth following the "green revolution" and the development of physical infrastructure (e.g. roads, highways, and bridges) and communication technology (e.g. cell phones, the Internet, etc.) have expanded the non-farm sector significantly beyond urban areas. The clear demarcation between the urban advanced sector and the rural farm economy is disappearing fast in many developing countries. Thus, farm household members can work both in the farm sector and the non-farm sector simultaneously; working in the non-farm sector no longer requires the farm household to move its working members to urban areas, either permanently or temporarily. A farm household may relocate its labor endowment between farm and non-farm uses through optimization behavior as an economic agent; an individual from a farm household may work in the non-farm sector

either part-time or full-time. As an agricultural economy experiences significant shocks and readjustment, the relocation patterns of a farm household's labor endowment are critical characteristics of the rural labor market development, and this issue has drawn attention from many economists (see Sumner, 1982; Huffman, 1991).

Much theoretical and empirical literature has investigated how a farm household may allocate its labor hours between farm and off-farm uses through optimization behavior (Sumner, 1982; Huffman, 1991; Mishra & Goodwin, 1997; and Goodwin & Holt, 2002). Much earlier literature on the off-farm labor supply of farm households has, however, focused on modeling and examining the off-farm labor supply effects on farming efficiency and farm income volatility. A similar question involves the extent to which the off-farm labor supply of farm households may change in response to agricultural mechanization, or the adoption of labor-saving technology. Despite its importance to the development process, the economic literature has not devoted sufficient attention to the joint analysis of farm households' decisions about labor supply to the non-farm sector in relation to the technology adoption decision.

The poverty outcomes and agricultural productivity outcomes of agricultural modernization have been studied extensively in the literature on agricultural mechanization (see David & Otsuka, 1994; deJanvry & Sedoulet, 2002; Evenson & Gollin, 2003; Minten & Barrett, 2008). Despite some earlier studies focused on the effects of agricultural mechanization on employment and wage earnings of poor and tenant farmers (Binswanger & Braun, 1991; The Nuffield Foundation, 1999; Minten & Barrett, 2008), the general labor market responses of farm households to agricultural mechanization have been overlooked. Farnandez-Cornezo, Hendriks, & Mishra (2005) find that the adoption of herbicide-tolerant

soybeans by farm households has positive effects on off-farm income. However, the herbicide-tolerant soybeans are not a labor-saving technology in the strict sense; they simply reduce management time. Ahituv and Kimhi (2002) find that farm capital investment reduces the farm households' participation in the off-farm employment opportunities, implying that family labor and farm capital are complements in agricultural production.

Over the last few decades, agriculture in most developing countries has undergone a significant structural transformation. Developing nations (except the nations in sub-Saharan Africa), have adopted labor-saving agricultural technologies at an unprecedented level. Intensification of production systems has created power bottlenecks around \ land preparation, harvesting, and threshing operations, even in the densely populated Asian countries; these power bottlenecks are alleviated with the adoption of labor-saving agricultural technology, which in turn raises agricultural productivity and reduces the per-unit cost of crop production (Pingali 2007). Tractors number in India rose from 0.19 per 1000 hectares in 1961 to 9 per 1000 hectares by 2000 (Pingali, 2007). Mandal (2002) estimates that, in Bangladesh, around 150,000 power tillers have been imported annually since liberalized import policies were implemented in the mid-1990s.

Mechanization has often been considered by the critics as detrimental for densely populated "labor surplus" countries, because of the negative effects of mechanization on agricultural employment in terms of displacement of labor and tenant farmers. If that argument is true, then what are the rationales of rapid mechanization of power-intensive operations even in Asian countries with high population densities and low wages, such as India, Bangladesh and the Philippines (Herdt, 1983; Pingali & Binswanger 1987)? Existing evidence indicates

instead that the mechanization of power-intensive operations (water lifting, tillage, milling, etc.) have minimal labor displacement effects (Pingali 2007). Hormozi, Asoodar, & Abdeshahi (2012) find a strong positive correlation between agricultural mechanization and the technical efficiency of rice producers in Iran. The productivity effects of agricultural mechanization can come from three sources: yield changes, area expansion, and labor savings. The evidence presented in the literature indicates that, for power-intensive operations, generally no significant yield difference exists between animal draft and tractor tillage (Herdt, 1983; Binswanger, 1978). If we find no yield differences between animal draft and tractor farms, we must conclude that the transition to tractor-drawn plows is rarely motivated by improvement in tillage quality. Area expansion and/or labor saving must be the driving forces for such a transition. In densely populated countries, the ability to expand the area under cultivation is extremely narrow, which is clearly indicated by the tiny amount of arable land per agricultural worker (for example, 0.26 hectare per worker over 2006–2011 in Bangladesh, according to the Food and Agriculture Organization [FAO]).

The evidence presented in the literature indicates that, for power-intensive operations, the productivity benefits of mechanization consist mainly of labor savings. Pingali, Bigot, and Binswanger (1987) reviewed 24 studies on labor use of farm households, and 22 of the 24 studies reviewed reported lower total labor use per hectare of crop production for tractor farms compared to draft animal farms. Twelve studies reported reductions in labor use of 50% or more. The greatest reduction in labor use was for land preparation, which was reduced by 50% or more. These results indicate that labor savings resulting from the transition to tractors are confined mainly to land preparation. A natural question follows: to what use has the labor saved

through agricultural mechanization been put? The answer to this issue has been hypothesized in the relevant literature to be non-farm use.

Excellent non-farm employment opportunities may induce farm households—even those in densely populated countries with land scarcity—to mechanize farm operations. Cultivators became prevalent in Japan during the late 1950s, when agricultural wages rose sharply in response to high labor demand from post-war industrialization (Ohkawa, Shinohara, & Umemura, 1965). In recent decades, fast-growing south Asian countries like Bangladesh and India have shown a similar trend, experiencing significant rural labor market tightening with a pronounced increase in rural real wages (Hnatkovska & Lahiri, 2013; Hossain, Sen, & Sawada, 2013). The use of labor-saving technology (e.g. tractors, threshers, etc.) in agriculture, and the rapid expansion of the non-farm sector have enabled farm households to reallocate their underemployed agricultural labor time toward more highly productive off-farm work in the non-farm sector.

This chapter examines whether agricultural mechanization could induce farm households to participate in, and to supply more labor hours in, the non-farm sector. Existing literature about farm households holding multiple jobs has mainly studied the United States and other developed countries (see Goodwin & Holt, 2002; Goodwin & Mishra, 2004). Research on farmers in low-income countries holding multiple jobs is scarce. Moreover, there has been little research into how farm households' adoption of labor-saving technology affects the off-farm labor supply. This chapter uses a unique longitudinal survey data set from rural Bangladesh to investigate the role of the labor-saving technology adoption in farm production on the non-farm labor supply decisions of farm households. An agricultural household model

is used to establish the relationship between labor-saving technology adoption and the off-farm labor supply decisions of farm households through the elasticity of substitution between labor and capital in agricultural production.

The increase of market-based rentals of agricultural technology in Bangladesh brings the benefit of modern technology within the reach of subsistence farm households. For example, about 89% of farm households use tractor or power tillage for land preparation in agricultural production, while only 5% farm households own a tractor/power tiller. This structural shift has changed the input ratios used in farm production. A tractor/power tiller is regarded as labor-saving technology, and the use of tractor/power tillage reduces the labor requirement in land preparation, thus releasing extra labor hours. Thus, the joint analysis of agricultural households' decisions regarding the adoption of labor-saving technology and their off-farm labor supply will add additional knowledge to the relevant literature. The adoption of mechanized technology raises agricultural productivity, which in turn increases returns to time employed in farming. Thus, an income effect could increase the farm operator's leisure time, while a substitution effect could raise the amount of time used in farm production. Because most farming in developing countries is subsistence farming, and because of extremely low arable land per capita, the ability for most farm households to raise work hours in the farm sector is somewhat limited. Thus, the farm operator may instead supply labor hours in the non-farm sector as long as returns from the non-farm sector are higher than the opportunity cost of leisure time. Through this dynamic, the adoption of mechanized technology in farming could lead to a higher supply of labor hours allocated to the non-farm sector by a farm household.

The population density in Bangladesh is the highest in the world, and the challenge to agricultural livelihoods is clearly indicated by the tiny amount of arable land per agricultural worker (0.26 hectare per worker over 2006–11, according to FAO). Certainly, rural farm households need to diversify their income sources and livelihood strategies, both to manage risks and to ensure more rapid income growth. The evidence suggests that such diversification is well underway in Bangladesh (Sen, 2003; World Bank, 2016). While absolutely and functionally landless households depend on the rural non-farm economy for their survival, farm households are also increasingly engaging in non-farm economic activities, both to diversify the risks of farm income volatility from price shocks and production loss, and to smooth consumption in the lean season.

The main objective of this study is to explore the impact of agricultural mechanization on the labor supply behavior of farm households. Specifically, it examines the off-farm participation effects of the adoption of labor-saving farm technology. This chapter looks at the joint decisions of off-farm labor supply and the labor-saving technology adoption of farm households using primary data obtained from a nationally representative longitudinal survey data for the years of 2000 and 2008.[2]

The rest of the chapter is organized as follows. Following the introductory discussions in Section 1.1, Section 1.2 outlines the conceptual and theoretical framework. Section 1.3 describes the econometric model employed for estimation; Section 1.4 presents and discusses data sources, sampling strategy, and summary results; and Section 1.5 presents the results of

[2] For detailed survey results and sampling strategy, see Hossain and Bayes (2009).

econometric models and the analysis of the results. The chapter ends with concluding remarks and policy implications in section 1.6.

1.2. Theoretical Model

The chapter uses the agricultural household model, developed by Singh, Squire, and Strauss (1986) and modified by Sadoulet and deJanvry (1995), to establish the relationship between the labor-saving technology adoption decision and the off-farm labor supply decision through the elasticity of substitution between labor and capital in farm production. Goodwin and Holt (2002) and Farnandez-Cornejo et al. (2005) modified this agricultural household model to study the off-farm labor supply decisions of farm households in Bulgaria and the United States, respectively. We use the Goodwin and Holt (2002) and Farnandez-Cornejo et al. (2005) version of the agricultural household model, introducing the agricultural technology adoption decision into the production techniques, to identify the off-farm labor supply function of farm households. The significant difference between this study and the earlier works of Goodwin and Holt (2002) and Farnandez-Cornejo et al. (2005) is that we treat the farm household as an economic agent instead of a farm operator. This is because the independence among individuals within the same household could not be assumed; household members' economic decisions are jointly determined. The labor supply decisions of rural farm households in developing countries are governed by the household's utility maximization problem, which is subject to constraints on total time endowment, income, and farm production technology. Households' members are assumed to receive utility from a vector of members' leisure and non-economic activities at home (l), a vector of purchased goods (q), and a vector of household characteristics (z), such as human capital, age, and household size, that are

exogenous to the household's decisions. Farm households maximize utility (U) subject to income, technology, and time constraints. The agricultural household utility function can be modeled as

$$U = U(q, l; z) \tag{1.1}$$

where U is assumed to have the usual regularity properties of a utility function, such as twice differentiability, quasi-concavity, and increasing in q, l, and z. Farm households generate utility from consumption of good q; from leisure l, which also includes home time; and from other household characteristics z, such as human capital, age, household size, and so on. The model assumes that marginal utility of consumption good and leisure approaches infinity as consumption goes to zero, which ensures that a positive amount of consumption good and leisure are always consumed.

The objective of the farm household is to maximize utility from the consumption of goods and leisure subject to the farm production, income, and time constraint. The income, farm production technology, and time constraints can be represented as

$$p_c q + rX(T) = p_f Q + wM \text{ \{Income constraint\}} \tag{1.2}$$

$$Q = Q\{X\ (T), F(T), D)\} \text{ \{Technology constraint\}} \tag{1.3}$$

$$H = M + F(T) + l \text{ \{Time constraint\}} \tag{1.4}$$

Equation (1.2) is the household's income constraint, where p_c is the consumer price of q; p_f is the unit price of output; w is is the wage rate for non-farm works; X is the vector of other inputs, such as land, capital, fertilizers, etc.; and r is the column vector of prices of inputs

in X. M denotes the labor time spent in off-farm work. Unlike Goodwin and Holt (2002) and Farnandez-Cornejo et al. (2005), we exclude income from other sources (e.g. capital gains, interest income, etc.) in our income constraint, as income from other sources is rare among Bangladeshi farm households. Farm income depends on the price of agricultural output, p_f; on input prices, r; and on the amount of time spent on farm works, F.

Equation (1.3) represents a household's technology constraint, where F is labor time devoted to the farm and T stands for the farm household's labor-saving technology adoption decision. The adoption of labor-saving technology reduces the labor requirement in farm production. Thus, the adoption of agricultural technology should be incorporated into the production technology implicitly, not as a shifter of the production function. D is a vector of exogenous factors that shift Q. The production technology is assumed to have all the regularity conditions, such as twice differentiable, increasing in inputs, etc.

Equation (1.4) is the time constraint of the agricultural household. Each household has a fixed amount of time, H, which is allocated among farm work, off-farm work, and leisure. This agricultural household model assumes that marginal productivity of farm labor approaches to infinity while on-farm work is zero, implying interior solution of the model, $F > 0$. However, off-farm labor works, M, could be zero as well, $M \geq 0$.

Plugging (1.3) into (1.2), we combine the technology and the income constraint into the following constraint:

$$pq + rX(T) = p_f Q(X(T), F(T), D) + wM + A \qquad (1.5)$$

Now we can solve the agricultural household model, given the differentiable utility function and given λ and μ as the Lagrange multipliers of the income and the time constraints, respectively:

$$L = U(q, l, d) + \lambda\left[p_f Q(X(T), F(T), D) + wM + A - pq - rX(T)\right] + \mu[H - M - F(T) - l].$$

The Kuhn-Tucker first-order conditions are:

$$\frac{\partial L}{\partial q} = U_q - \lambda p = 0 \tag{1.6}$$

$$\frac{\partial L}{\partial l} = U_l - \mu = 0, \tag{1.7}$$

$$\frac{\partial L}{\partial T} = \lambda\left[p_f \left\{\left(\frac{\partial Q}{\partial X}\right) * \left(\frac{\partial X}{\partial T}\right) + \left(\frac{\partial Q}{\partial F}\right) * \left(\frac{\partial F}{\partial T}\right)\right\}\right] - r\left(\frac{\partial X}{\partial T}\right) - \mu\left(\frac{\partial F}{\partial T}\right) = 0 \tag{1.8}$$

$$\frac{\partial L}{\partial X} = \lambda[\, p_f \frac{\partial Q}{\partial X} - r] = 0 \tag{1.9}$$

$$\frac{\partial L}{\partial F} = \lambda\, p_f \frac{\partial Q}{\partial F} - \mu = 0 \tag{1.10}$$

$$\frac{\partial L}{\partial M} = \lambda w - \mu \leq 0, M\,(\lambda w - \mu) = 0 \tag{1.11}$$

$$\frac{\partial L}{\partial \lambda} = p_f Q(X(T), F(T), D) - wM + A - pq - rX = 0 \tag{1.12}$$

$$\frac{\partial L}{\partial \mu} = H - M - F(T) - l = 0 \tag{1.13}$$

Given the positive amount of labor supply to off-farm work, an interior solution occurs and equation (1.10) and (1.11) hold with equalities. From equation (1.10) and (1.11), we can reach a familiar condition:

$$p_f \frac{\partial Q}{\partial F} = w \tag{1.14}$$

The marginal value of the farm labor must be equal to the off-farm wage rate. Solving equations (1.6), (1.7), and (1.11) would give us another familiar condition:

$$\frac{U_q}{U_l} = \frac{p}{w} \tag{1.15}$$

The condition in (1.15) implies that the marginal rate of substitution between consumption and leisure should be equal to the ratio between the price of consumption good and the wage rate.

When an interior solution occurs, equations (1.9) and (1.10) can be solved independently to obtain farm labor demand as optimal consumption, and production decisions can be separated because the value of the household's time is determined by the off-farm wage rate: ($w = \frac{\mu}{\lambda}$) (Huffman, 1991).

Solving the model, we could find following on-farm labor demand functions and input demand functions:

$$F^* = F(r, w, p_f, T, D) \tag{1.16}$$

$$X^* = X(r, w, p_f, T, D) \tag{1.17}$$

Substituting these optimal input demand functions into the technology constraint (1.3) would give us optimal output, as follows:

$$Q^* = Q(r, w, p_f, T, D) \quad (1.18)$$

Solving jointly equations (1.6), (1.7), (1.12), and (1.18), a household's optimal amount of leisure demand and consumption good can be derived as follows:

$$l^* = l\,(r, w, p_c, p_f, T, D) \quad (1.19)$$

$$q^* = q(r, w, p_c, p_f, T, D) \quad (1.20)$$

Plugging optimal leisure hours and on-farm labor demand into the time constraint, the derived supply of off-farm labor (Huffman, 1991) is as follows:

$$M^* = H - F^* - l^*$$

$$= M(r, w, p, p_f, T, D, z) \quad (1.21)$$

Equation (1.21) implies that, given a constant total amount of labor endowment of a farm household, the adoption of labor-saving technology in agricultural production would result in a higher level of labor supply to the non-farm sector.

1.3. Econometric Methodology

The goal of this chapter is the estimation of the off-farm labor supply decisions of farm households, rather than the explicit estimation of a structural labor supply model of a farm

household.[3] Therefore, we follow a simple reduced-form model of off-farm labor supply to estimate the effects of agricultural mechanization on the off-farm labor supply decisions. The theoretical framework for the model of off-farm labor supply decisions suggests that all observable farm household characteristics that affect wages, prices, production, and utility should be included in the estimation of off-farm labor supply decisions.

To estimate the non-farm participation effects of the adoption of labor-saving agricultural technology, we use following regression specification based on the theoretical background given in the preceding section:

$$P_{it} = \alpha + \beta X_{it} + \delta Z_{it} + \rho_t + \varepsilon_{it} \tag{1.22}$$

P_{it} denotes the participation/labor supply of ith household in the rural non-farm (RNF) sector at year t. X_{it} is a vector that includes number of variables representing households' and workers' characteristics. Z_{it} attributes a household's agricultural technology adoption status. Year-specific effects are represented by ρ_t, while ε_{it} stands for idiosyncratic normally distributed error terms.

Two separate versions of the model (1.22) need to be used to estimate the effects of the adoption of labor-saving technology adoption by farm households on their off-farm labor supply decisions. The first version models the participation decision and the second set models the magnitude of labor supply to the off-farm work. An ordinary least square (OLS) estimation of linear probability model (LPM) or the maximum likelihood estimation of probit of equation

[3] Mishra and Goodwin (1997) and Goodwin and Holt (2002) also estimated a simplified reduced-form model rather than estimating a structural model of labor supply.

(1.22) can estimate the impact of the technology adoption on the non-farm participation decision. Similarly, an OLS, or the maximum likelihood estimation of endogenous treatment effects (ETE) of equation (1.22), can estimate the impact of technology adoption on the extent of non-farm labor supply. The participation decision model of equation (1.22) can be presented as follows:

$$P_{it}^{*} = \alpha + \beta X_{it} + \delta Z_{it} + \rho_t + \varepsilon_{it} \quad (1.23)$$

Where $P_{it}^{*} \geq 0$ if $P_{it} = 1$

$P_{it}^{*} < 0$ if $P_{it} = 0$

Where P_{it} stands for the non-farm participation (NFP) decision (probit). P_{it}^{*} is a latent variable that is unobserved if P_{it}^{*}<0.

The labor supply decision model of equation (1.22) can be presented as follows:

$$P_{it} = \alpha + \beta X_{it} + \delta Z_{it} + \rho_t + \varepsilon_{it} \quad (1.24)$$

Here, P_{it} stands for the labor supply decision.

Estimating the impact of technology adoption on the participation and the labor supply behavior of farm households, however, presents some difficulties. When the unobserved households' characteristics (e.g. skill and abilities of workers) are correlated with both the off-farm work decision and the technology adoption decision, spurious correlations might be produced, which might give biased estimates of the effects of technology adoption on the off-farm participation decision. Moreover, farm households with partial or full involvement in the

non-farm sector can adopt labor-saving technology to substitute the foregone labor hours that are supplied to the non-farm sector. Thus, the OLS regression of the off-farm work decision on the technology adoption decision might be capturing the positive "effect" of reverse causality. Though the workers' schooling may capture their capacity and skill to some extent, it is, in general, not possible to control for all such potential confounding factors in a regression specification, and thus regression results that do not account for endogeneity may be misleading. To control for the possible endogeneity between the technology adoption decision and the off-farm labor supply decision, an instrumental variable (IV) approach is used to estimate the relevant models of equation (1.23) and (1.24).

For the participation equation, the study follows three standard econometric methods: the instrumental variable (IV) approach, the bivariate probit model (BPM), and the endogenous switching probit model (SPM). While the IV approach with a binary dependent variable may encounter the limitations of a linear probability model (LPM), the IV version of the LPM model facilitates several tests that examine the validity of the relevant instruments, and we expect that the validity tests of instruments will be untroubled by the limitations of LPM in the IV model. However, the main results regarding the non-farm participation effects of labor-saving technology adoption are drawn from the BPM and the SPM, which are particularly designed for dealing with a binary dependent variable with endogenous dummy treatment variables. Both the BPM and the SPM rely on normality assumptions. The SPM, however, is more efficient, as it relaxes the participation equation's assumption of equality of coefficients in two regimes. We have estimated both models for two reasons. First, the BPM provides average marginal effects (hereafter, AME) of all the covariates in the participation equation, as well as the average treatment effects (hereafter, ATE) of the technology adoption; retrieving marginal

effects for all the covariates is a cumbersome process in the SPM. Second, the SPM provides regime-specific coefficients for all the covariates, which offers insight into the regime-specific role of covariates; in contrast, the BPM assumes equality of coefficients in the participation equation across the regimes. Moreover, estimating both models helps us to check the robustness of the estimates of ATE.

For the same reasons, we also follow the two standard econometric approaches (the IV approach and the ETE model) with the labor supply equation. Although the use of a linear IV model with an endogenous dummy regressor is inefficient, we use this model to check the validity of instruments. Given the binary nature of the endogenous regressor that represents the labor-saving technology adoption decision, the ETE model is the most efficient one for estimating the labor supply effects of the technology adoption in farm production. The ETE model also allows censoring the sample for which the non-farm labor supply is not observed.

Given the longitudinal nature of the data set used for this chapter, the use of the fixed-effects model would be ideal. But the fixed-effects model suffers the "incidental parameter problem" and excludes the variables that do not vary over time. However, Mundlak (1978) has shown that, for balanced panel data, the fixed-effect estimator can be generated from pooled OLS estimators by adding the time means of the covariates as additional explanatory covariates. Wooldridge (2013) extends the work of Mundlak (1978) to unbalanced panel data and nonlinear panel data models. Thus, we follow correlated random effects (CRE) estimation for each specification to avoid the incidental parameter problem and to get the fixed-effects estimate for variables that vary over time and across households.

1.3.1. Identification Strategy

The initial challenge to establishing the causal impact of the technology adoption decision on non-farm participation decisions is the possibility of unobserved characteristics of farm households that simultaneously affect their non-farm participation decisions and their technology adoption decisions. For example, farm households with educated working members may participate in the non-farm sector to diversify their earning sources, and may adopt modern agricultural production technology to substitute their foregone labor hours. A simple comparison between the percentages of non-farm participation among the technology-adopting farm households and the non-adopting farm households would overstate the non-farm participation effects of the adoption of labor-saving technology. Alternatively, small or marginal farm holdings, which may not be appropriate for the use of labor-saving technology, may forego participation in the rural non-farm sector because of labor constraints, which might lead to a spurious negative relationship between farm households' non-farm participation decision and technology adoption decision. Therefore, the direction of selectivity bias is theoretically uncertain.

We therefore follow the IV approach to reduce selectivity bias. We use village-level average rainfall in the previous 10 years, the presence of operating land with clay loam soil, and operating land with a very high level of elevation as instruments for the likelihood of a household's adoption of tractor or power tiller for land preparation in farm production. Higher rainfall makes the tillage process easier, inducing farm operators to rely less on mechanized tillage and more on family labor and cattle/bullocks for land preparation. Heavy rainfall also reduces the use of tillage due to runoff and soil losses (Munodawafa, 2012). Land with clay

loam soil is difficult to till, thus inducing farm operators to use mechanized tillage. A household with clay loam soil is 3% more likely to use mechanized tilling than a household without clay loam soil. Land with high elevation is close to homestead land and thus induces households not to use hired mechanized tillage, and to instead use family labor and cattle/bullocks for tilling. Farm households that operate land with high elevation are less likely to adopt mechanized tillage. Thus, the use of rainfall, soil quality, and land elevation are valid instruments for a household's mechanization decision.

Our identification strategy is that all these instruments, apart from their influence on the households' tractor/power tiller use, do not affect the non-farm participation decision of a farm household. Instrumental variable estimation relies on this exogeneity assumption. Thus, the validity of the instruments is crucial for reliable estimates. One potential threat is that rainfall in a village might influence farm productivity, which in turn affects the non-farm participation decision, which in turn affects the technology adoption decision. Considering this possibility, we control for the farm productivity by incorporating gross margin in farm production of each farm household. The validity of the instruments has been checked as well, and the instruments have passed all the relevant tests for weak identification and overidentification.

1.4. Data and Summary Statistics

The data for this study are drawn from a unique longitudinal survey of a nationally representative sample of rural households in Bangladesh. The survey spanned about two decades (1988–2008) and was conducted to assess changes in rural poverty and livelihoods in response to technological progress, food price hikes, etc. The baseline survey was administered

by the Bangladesh Institute of Development Studies (BIDS) in 1988.[4] It included 1,240 rural households from 62 villages in 57 out of 64 districts in Bangladesh and studied the impact of technological progress on income distribution and poverty in Bangladesh (Hossain, Quasem, Jabbar, & Akash, 1994; Rahman & Hossain 1995). The households were revisited in 2000, 2004, and 2008. However, we could access only data for 2000 and 2008; therefore, this study limits its analysis to the 2000 and 2008 data. The sample size in the repeat surveys of 2000 and 2008 were 1880 and 2010, respectively. The information was collected through a semistructured questionnaire designed to gather information on demographic details, land use, costs of cultivation, livelihoods, farm and non-farm activities, commodity prices, ownership of non-land assets, income, expenditure, and employment. In addition to these data, the dataset provides extensive details of the farms' characteristics, including details on soil type, elevation, irrigation sources, and tenurial arrangements, among others.

To study the off-farm labor supply effects of agricultural technology adoption using a panel survey, the problem of the splitting of households needed to be addressed, as household-splitting makes it difficult to compare the households' performances over time. Splitting of households is a very common scenario in rural Bangladesh, especially after the death of the household head, typically the father. Thus, the splitting of the household has serious implications for land and other non-land asset endowments. Among the original 1880 sample households that were surveyed in 2000, 1598 households (about 85%) remained intact

[4] The benchmark survey used a multistage random sampling method. The sample size has been adjusted in each round of survey to make the sample representative to the rural population for the survey year. In the first stage, 64 unions were selected randomly from the list of all unions. In the second stage, one village was selected from each of the unions that best represented the union in terms of population density, land distribution, and literacy rate. Two villages were later excluded because their remoteness made it difficult to administer the survey. A census of households was conducted in the selected villages to stratify the households according their landownerships, land tenure, and literacy.

throughout the period of 2000–2008. Thus, household splitting and attrition from migration occurred at a rate of nearly 1.9% per year for the period of 2000–08. Among the 1598 intact households, we use 852 sample households in our analysis; the rest of the households were not involved in farm production in either 2000 or 2008.[5]

The main advantage of the 62-village panel survey over repeated cross sections (such as Household Income and Expenditure Survey (HIES) or Labor Force Survey (LFS)) is the ability to track the employment status of the same household over time. Looking at the multiple cross-section surveys (for example, HIES and LFS), there is little movement of rural labor forces between the farm sector and the non-farm sector. Between 2000 and 2010, according to the Bangladesh Bureau of Statistics (BBS), the share of the RNF sector in total rural employment has increased by only 1%, from 44.5% in 2000 to 45.5% in 2010 (BBS, 2013). This number, which is based on the repeated cross-section surveys, shows that the net movement of the rural workforce between farm and non-farm activities often fails to capture the ultimate employment dynamics in rural Bangladesh. Analysis of labor supply decisions of farm households based on longitudinal data is thus not just about capturing employment trends; it enables us to look beyond mere statistical aggregates and shed light on causalities of long-term employment patterns. The panel waves capture the decisions of the same households over time. This leads to better understanding of the possible policy support necessary to further support the movement of the rural workforce toward better non-farm opportunities.

[5] The inclusion of the ‘‘split households’’ creates difficulties in estimating changes in the asset base of the household, an estimation that is crucial to the application of the livelihood framework attempted in this paper. Given the focus of the present paper on understanding the ‘‘drivers of change’’ with respect to those who did and did not participate in the non-farm sector, the exclusion of the split households does not make a critical difference.

The panel nature of the data allows us to identify several dynamic-employment groups on the basis of their diverse movements in and out of the non-farm sector. For the purpose of analyzing employment dynamics, we have generated two groups of households based on their work status. Sample farm households that remain exclusively in farming (all the working members of a household are involved in agricultural activities only) are categorized as "farm only," while the farm households that also engage in non-farm activities (any of the working members of the household are involved in any kind of non-farm activities)[6] are considered as "non-farm participants." Patterns of participation in the non-farm sector and transformation over time are presented in Table 1.

Table 1 reveals a strong mobility between the farm sector and the non-farm sector throughout the period of 2000–2008. A significant portion of sample households moved back and forth between the farm-only status and the non-farm participant status; from 2000 to 2008, there were 338 households (39.7% of the total sample of 852 households) that retained farm-only status, while 212 households (24.9% of the total sample) remained non-farm participants (Table 1). The other two categories indicate the changing employment patterns: one group initiated participation in non-farm activities, while the other pulled themselves out of non-farm activities and returned to farm-only status. In the same period, 133 households (15.6% of 852 households) initiated participation in non-farm economic activities and 169 households (19.8% of the total sample) moved out of non-farm activities.

[6] Farm activities include farming, fishing, poultry and livestock rearing, forestry, and agricultural wage labor. Non-farm activities include transportation, services, and entrepreneurships.

Two immediate observations follow from the above discussion. First, gross movements of the rural workforce between farm and non-farm activities are much larger than the net changes in the sectoral employment trends over time reveal. Second, it is important to study the drivers of change underlying the movements of rural households between farm and non-farm activities to understand better the causes of movements of rural workforce toward non-farm economic opportunities. Studying these movements provides deeper insights into the mechanisms that boost the participation of rural households in the non-farm sector than merely studying the characteristics of the non-farm participants over time, and may provide avenues for attacking the underemployment of family labor in farm production in developing countries.

Table 1: Transition Between Work Statuses

			Work status in 2008		
			Worked only on-farm	**Worked off-farm**	**Total**
	Worked only on-farm	*N*	338	133	471
		Percent	39.67	15.61	55.28
Work status in 2000	Worked off-farm	*N*	169	212	381
		Percent	19.84	24.88	44.72
	Total	*N*	507	345	852
		Percent	59.51	40.49	100

Table 1 relates the labor-saving technology adoption decision to the non-farm participation decision of farm households. The probability of participating in the rural non-farm sector is the highest (0.42) for households that remained users of agricultural technology throughout the period between 2000 and 2008; the probability is lowest (0.31) for households that remained non-users of agricultural technology throughout the same period. The likelihood

of non-farm participation is also higher for households that changed their status from non-adopters of agricultural technology in 2000 to users in 2008 than in households that remained non-users in 2008. The bar chart also shows that households that adopt labor-saving agricultural technology work more in the non-farm sector than do households that do not adopt the labor-saving agricultural technology. Farm households that remained users of agricultural technology between 2000 and 2008 worked, on average, 133 days in the rural non-farm sector; households that didn't adopt the labor-saving land-preparation technology in the same period worked, on average, 107 days in the rural non-farm sector. Households that moved from being non-users of agricultural technology for land preparation to being users of this technology between 2000 and 2008 worked, on average, 114 days in the rural non-farm sector. On the other hand, households that were technology users in 2000 and were not technology users in 2008 work the lowest average amount of time (only 76 days) in the rural non-farm sector.

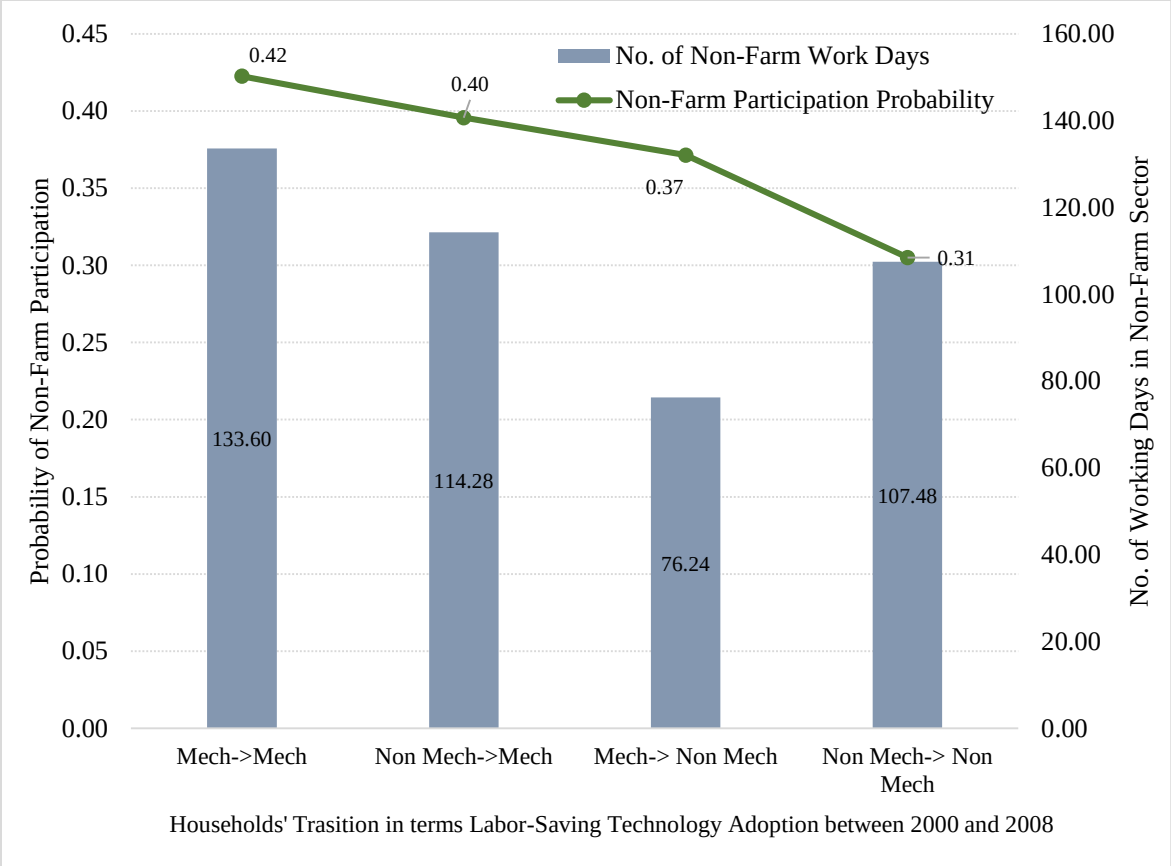

Figure 1. Households' transition to and from the use of labor-saving agricultural technology between 2000 and 2008.

Summary statistics of the key variables are provided in Table 2. As Table 2 shows, the mean age of household head increases over time regardless of the sector of employment. Households with more working members, higher family size, and greater female labor force participation are more inclined to participate in the rural non-farm sector. These statistics imply that households with more working members are more likely to diversify their employment out of agriculture. As expected, schooling helps rural households to move out of farming and to get into non-farm sector opportunities. For households working only on-farm, the average number of years of school attended was around four between 2000 and 2008; for households

that participated in the non-farm sector during the same period, the figure was around five years of school.

The likelihood of non-farm participation of rural farm households is found to be sensitive to the initial asset position, e.g. the amount of land owned (Table 2). For the period from 2000 to 2008, the proportion of households that participated in the non-farm sector remained almost stagnant for the categories of marginal/small and large landowners; it declined for the medium landowner category; and it increased for the absolutely/functionally landless households. The propensity of NGO membership was higher among the non-farm participant households than the farm-only households; the difference was about 10% between 2000 and 2008. The returns from agricultural land and family labor (proxied by gross margin of farm production) were slightly lower in 2000 for households with non-farm participation than the households with farm only status. However, the gross margin of agricultural production for the non-farm participant households was 30% higher in 2008 than that of the farm-only households. Land fragmentation often is to blame as a source of inefficiency in farming; high land fragmentation requires more labor time, as it is time-consuming to travel between plots. Here we find that land fragmentation was higher among the farm households that remained exclusively in farming in both years.[7]

Table 2 also presents summary statistics for the instruments used in the estimation. The rainfall was usually lower for households that participated in the RNF sector. The proportion

[7] The land fragmentation index is constructed following the formula of Simpson's concentration index as follows:

$$S = 1 - [\sum_{i}^{n} \left(\frac{a_i}{\sum a_i}\right)^2]$$

where a_i is size of a plot i. The index, S, is constructed as such that higher value implies more fragmented.

of farm households with clay loam land was higher among the participant households than non-participant households. The likelihood of having land with high elevation was greater among the farm-only households than the non-farm participant households in 2000; this was reversed in 2008.

The age of the farm household head may represent a general experience that increases the marginal value of time in each activity, and younger household heads are expected to participate more in the non-farm sector. The sign of the age variable is thus expected to be negative. Having more than one working member in the family may have a positive effect on non-farm labor participation. Larger household size may have either positive or adverse effects on non-farm labor participation. Female labor force participation is expected to have a positive effect on non-farm labor participation. Farm operators' educational qualifications may positively affect non-farm labor participation. Land ownership may be negatively related to non-farm labor participation, because having less land may require less labor in farming, which in turn may induce the farmer to work in the off-farm sector. Both land fragmentation and the gross margin from farming are expected to have adverse effects on non-farm labor participation.

The propensity of households to participate in the non-farm sector is also found to be associated with households' technology adoption, as non-farm participant households are more likely to adopt the technology. The adoption rates are 63% and 88% among the households with farm-only status in 2000 and 2008, respectively; among the non-farm participant households, the adoption rates are 69% and 91% in 2000 and 2008, respectively.

Table 2: Descriptive Statistics of the Covariates

Variables	Households with farm only workers 2000	2008	Households with both farm and non-farm workers 2000	2008
Mean age of household head	45.14	48.61	46.38	50.67
Mean household size	5.54	5.06	6.27	5.95
No of adult working member (% of households)				
One working member	64.10	64.89	49.87	39.13
Two working members	21.66	23.47	25.98	31.88
Three or more working members	14.23	11.64	24.15	28.99
Female worker in household (% of households)	2.55	6.71	5.25	13.62
Landownership (% of households)				
Abs/functionally landless (<0.4 ha)	47.77	52.86	50.39	52.46
Marginal/small landowner (> = 0.4 ha & <1.0 ha)	28.03	29.59	23.10	23.19
Medium landowner (> = 0.1 ha & <2.0 ha)	16.99	13.02	16.80	14.49
Large landowner (> = 2.0 ha)	7.22	4.54	9.71	9.86
Workers' average years of schooling	4.03	3.91	4.64	5.80
Mean gross margin per hectare (in thousand Tk. In 2008 prices)	32.83	69.92	31.91	89.98
Mean cropping intensity	1.61	1.67	1.65	1.66
Mean of land fragmentation index	0.58	0.54	0.56	0.50
Proportion of NGO member households	0.21	0.32	0.31	0.42
Proportion of households that adopt tractor in land preparation	0.63	0.88	0.69	0.91
Mean annual rainfall (in mm) in the last ten years	1530	1532	1512	1522
Proportion of households with clay loam land	0.25	0.30	0.29	0.33
Proportion of household with high land	0.54	0.32	0.47	0.34

1.5. Results and Discussion

1.5.1. Participation Equation

This section presents the results from the estimation of the participation equation. First, an instrumental variable (IV) model is used, despite its limitation with the use of binary outcome variables, to examine the validity of the relevant instruments. The estimates from both the first and second stages of IV, along with many other test statistics, are reported in Table 3. The endogeneity of the technology adoption decision needs to be checked, and both the

Durbin's score statistics and the Wu-Hausman test reject the hypothesis that the technology adoption decision of a farm household is exogenous to the off-farm participation decision of that household. For the validity of instruments for an endogenous regressor, instruments must pass the orthogonality condition (that instruments are orthogonal to the outcome variable). All three instruments pass Sargan's orthogonality test, because the test statistics fail to reject the null hypothesis of the instruments' orthogonality to the non-farm participation decision. Besides being orthogonal to the outcome variable, instruments also must be correlated with the endogenous regressor. In likelihood-ratio (LR) IV redundancy tests, the null hypothesis of an instrument's redundancy has been rejected for each instrument. The instruments pass all the necessary tests (e.g. underidentification test, weak identification test, and overidentification test), indicating that they are valid instruments of the endogenous regressor.

Although the explanatory variables from the outcome equation are mostly statistically insignificant in the first-stage regression of determining the technology adoption decision, all the instruments are statistically significant. One percent more rainfall reduces the probability of the technology adoption by 0.3. All the relevant tests (Hausman, Wu-Hausman, and Durbin's score) confirm the presence of endogeneity between the non-farm participation decision and the technology adoption decision of farm households. The F-stat at the first-stage regression also passes the "more than 10" rule of thumb, implying that the excluded instruments are valid and significantly relevant. We have implemented the Montiel-Pflueger robust weak instrument test, as the large values of effective F statistics in this test correspond to small values of the approximate asymptotic bias (Pflueger & Wang, 2014).

All instruments pass the test, because the effective F statistic at 5% confidence level (17.5) is well above the generalized two-stage least square (TSLS) critical value at 5% worst-case bias (13.42). Thus, the use of rainfall, soil quality, and land elevation as instruments for the adoption of tractor/power tiller in land preparation does not suffer the usual weak instrument problems.

The results in the second stage indicate that the adoption of labor-saving tillage systems raises the probability of non-farm participation by 0.46. Thus, the impact of technology adoption on the non-farm participation of farm households is quite high. As we are aware of the limitations of LPM, we should use these results with caution. Although all predicted probabilities remained within the band of unity, the disturbances were not homoscedastic. Thus, the coefficients that are presented in Table 2 are unbiased but not consistent. To overcome this consistency problem, we use a probit model with robust standard errors.

Table 3: IV Estimates and the Results of the Tests of Validity of the Instruments

	Instrumental variable (IV) 2SLS model			
	Non-farm participation equation		Mechanization equation	
	Coeff.	*SE*	Coeff.	*SE*
Mechanized (yes = 1)	0.460***	(0.162)		
Age of household head	-0.001	(0.002)	-0.001	(0.002)
Household size	0.018**	(0.009)	0.008	(0.007)
Labor endowment dummies (ref: single working member)				
Two adult workers	0.097**	(0.038)	-0.049*	(0.030)
Three adult workers	0.149**	(0.061)	-0.051	(0.048)
Female participation in labor force (yes = 1)	0.086*	(0.051)	0.006	(0.041)
Log (total schooling years of workers)	0.012*	(0.007)	-0.006	(0.006)
Land endowment dummies (ref: marginal landowner (<0.4 Ha))				
Small landowner (> = 0.4 Ha & <1.0 Ha)	-0.015	(0.038)	0.025	(0.030)
Medium landowner (> = 1.0 Ha & <2.0 Ha)	0.021	(0.049)	0.007	(0.039)

Table 3: Continued

Large landowner (> = 2.0 Ha)	0.105	(0.067)	0.062	(0.054)
NGO membership (yes = 1)	0.121***	(0.027)	-0.014	(0.022)
Log (gross margin of farming in 2008 Tk.)	0.006	(0.015)	-0.004	(0.012)
Fragmentation index	-0.124	(0.079)	0.119**	(0.061)
Cropping intensity	0.019	(0.041)	0.005	(0.033)
Year dummy (2008 = 1)	-0.173***	(0.049)	0.244***	(0.022)
Correlated effects	Yes		Yes	
Instrument variables				
Log (mean rainfall in mm in last ten years)			-0.318***	(0.049)
Any cultivated land with clay loam soil? (yes = 1)			0.032	(0.021)
Any cultivated land with very high elevation? (yes = 1)			-0.058***	(0.020)
Constant	0.369***	(0.121)	2.73***	(0.368)
Wald chi2(21)	186.45***			
F(23, 1667)			10.40***	
R-squared	0.0211		0.135	
Observations	1691			
Underidentification tests (Ho: Model is underidentified) Anderson canon. corr. likelihood ratio stat Chi-sq(3) = 58.17 (*p* = 0.000)				
Weak identification statistics: (Ho: Instruments are weak) Cragg-Donald (N-L)*minEval/L2 F-stat = 119.77 (*p* = 0.00)				
Partial *R*-squared of excluded instruments: 0.0344 Test of excluded instruments: F(3, 1667) = 17.51 (*p* = 0.000)				
Tests of overidentifying restrictions Sargan (score) chi2(2) = 1.20 (*p* = 0.55) Basmann chi2(2) = 1.19 (*p* = 0.55)				
Tests of endogeneity: (H0: mechanization is exogenous) Durbin (score) chi2(1) = 5.2 (*p* = 0.02) Wu-Hausman F(1,1668) = 5.3 (*p* = 0.02)				
C statistic (exogeneity/orthogonality of suspect endogenous variable) Chi-sq(1) = 5.24 (*p* = 0.022)				
LR IV redundancy tests for instruments: (Ho: Instrument is redundant) Rainfall: Chi-sq(1) = 37.66***; Soil Quality: Chi-sq(1) = 2.85*; and Land elevation: Chi-sq(1) = 7.56**				
Sargan's Orthogonality tests for instruments: (Ho: Instrument is orthogonal to the outcome variable) Rainfall: Chi-sq(1) = 1.21; Soil Quality: Chi-sq(1) = 0.24; and Land elevation: Chi-sq(1) = 0.81				
IV heteroscedasticity test(s) using levels of Its only: (Ho: Disturbance is homoscedastic) Pagan-Hall general test statistic: Chi-so(23) = 39.09 (*p* = 0.04)				

Note. Standard errors are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As the IV estimation of the probit model is not a valid approach with an endogenous dummy covariate, the BPM and the SPM are used to estimate the off-farm labor supply effects

of the technology adoption decision. The bivariate probit helps to get the average marginal effects (AME) of each covariate along with the average treatment effects (ATE). On the other hand, the endogenous switching probit model (SPM) allows estimating of regime-specific coefficients of covariates in the participation equation. Results from the BPM are presented in Table 4; Table 5 presents the results from the SPM.

AME of technology adoption on the non-farm participation has been decreased to 0.31 in the BPM from 0.46 in the IV approach. In the BPM, the endogeneity issue between the technology adoption decision and the non-farm participation decision has been controlled through instrumenting the technology adoption decision. The goodness-of-fit test prefers the BPM over the separate probit equations, as the Wald test for $\rho = 0$ has been rejected at the 10% significance level, where ρ stands for the correlation coefficient between the residuals in the equations, and ρ equals zero implies that the model consists of two independent probit equations which can be estimated separately. The significant ρ implies that the exogeneity assumption cannot be met. The second goodness-of-fit test is Murphy's score test,[8] which embeds bivariate normal distribution within a wide family of distributions by adding more parameters to the model; it tests whether the additional parameters are all zeros using the score for the additional parameters at the BPM estimates. Despite its over-rejection tendency, the Murphy's score test fails to reject the hypothesis at a 5% significance level using asymptotic chi-square critical values,[9] which indicates that the BPM model fit well to the data.

[8] For detail about this test, see Chiburis, Das, & Lokshin (2011).

[9] Although Murphy (2007) suggested bootstrapping the critical values, Chiburis et.al. (2011) find that the asymptotic critical values work well enough even for small samples..

Specifically, the score test result indicates that the assumption of bivariate normal distribution of the error terms, which underlies the BPM, holds.

The results from the technology adoption decision have been discussed; the discussion of the results of the participation equation follows. The instrument variables were strongly significant for the technology adoption decision of farm households. The probability of adoption of labor-saving technology decreases by 0.29 for a 1% increase in the average rainfall of last ten years; having a plot with clay loam soil enhances the likelihood of mechanization by 5%; the ownership of plot with high elevation reduces the probability of technology adoption by 4%. Among other explanatory variables from the outcome equation, only fragmentation index was weakly statistically significant, with a positive coefficient in the adoption equation.

In the participation equation, most marginal effects appear statistically significant with the expected signs. The average marginal effect of mechanization on the probability of a household's non-farm participation is 0.35, implying that households that adopt labor-saving technology in farm production are 35% more likely to participate in the non-farm sector. The ATE is 0.33 and the average treatment effect on the treated (ATT) is 0.31. Both the ATE and the ATT appear statistically significant with positive signs. Bootstrapped standard errors with replications of 500 and clustered household IDs are used to determine the significance of the treatment effects. The results confirm that the adoption of labor-saving adoption raises the probability of participation in the non-farm sector.

Among other covariates, the variables that matter most for non-farm participation are demographic variables, human capital assets (average years of schooling of adult workers in

the family), and NGO membership. Physical assets endowment (e.g. landownership) weakly matters for the non-farm participation of farm households, as only the large farmers are more likely to participate in the non-farm sector. Age of household head appears with a negative sign, implying that the younger household heads are more likely to participate, but the magnitude was not statistically significant. After controlling for the number of adult workers in the family, the household size captures the impact of dependency ratios on the participation status of farm households. We find that increased household size also pushes households to participate in the non-farm sector significantly. Farm households with two adult workers and with three or more adult workers are more likely to take part in the non-farm sector by 8% and 12%, respectively. Extra working members in farm households allow that household to diversify income sources by working out of agriculture. Table 2 shows that, for the period between 2000 and 2008, the number of rural farm households' working members increased, and households with a higher number of working members are more engaged in the non-farm sector than their counterparts. Having female workers in the family is also positively associated with households' likeliness to participate in the non-farm sector. The presence of an active female worker in a family can raise the probability of participation in non-farm opportunities by 8%. Thus, bringing women, who make up half of the total adult population, into the workforce could boost the labor supply for the non-farm sector.

As expected, human capital assets, which are proxied by the average years of schooling of working members in the family, raise the likelihood of households' participation in the non-farm sector. A 1% increase in human capital assets enhances the probability that a household will participate by 1.1%. Thus, overall improvement of the rural workforce's educational attainment could lead to a higher level of rural workers' non-farm participation. Statistically

insignificant drivers of non-farm participation include farm households' landownership; gross margins, a proxy of the returns on land and family labor in agricultural production; cropping intensity; and the land fragmentation index, although the land fragmentation index appears with the expected negative sign.

The NGO membership of a household raises the probability of non-farm participation of that household by 11%. This result confirms that participation in microfinance programs raises the likelihood of involvement in the non-farm sector, which is a major goal of microfinance institutions in Bangladesh.

Table 4: BPM Marginal Effects Estimates

	Bivariate probit model			
	Non-farm participation equation		**Mechanization equation**	
	Marr. Eff.	*SE*	Marr. Eff.	*SE*
Mechanized (yes = 1)	0.349***	(0.101)		
Age of household head	-0.001	(0.002)	-0.001	(0.002)
Household size	0.018**	(0.008)	0.008	(0.006)
Labor endowment dummies (ref: single working member)				
Two adult workers	0.081**	(0.033)	-0.046	(0.030)
Three adult workers	0.122**	(0.055)	-0.045	(0.047)
Female participation in labor force (yes = 1)	0.077*	(0.046)	0.018	(0.039)
Log (total schooling years of workers)	0.011*	(0.006)	-0.006	(0.006)
Land endowment dummies (ref: marginal landowner (<0.4 Ha))				
Small landowner (> = 0.4 Ha & <1.0 Ha)	-0.009	(0.034)	0.028	(0.030)
Medium landowner (> = 1.0 Ha & <2.0 Ha)	0.020	(0.043)	0.014	(0.038)
Large landowner (> = 2.0 Ha)	0.101	(0.061)	0.077	(0.054)
NGO membership (yes = 1)	0.108***	(0.025)	-0.013	(0.021)
Log (gross margin of farming in 2008 Tk.)	0.005	(0.013)	-0.002	(0.012)
Fragmentation index	-0.106	(0.067)	0.103	(0.063)
Cropping intensity	0.015	(0.037)	0.021	(0.034)
Year dummy (2008 = 1)	-0.141***	(0.033)	0.234***	(0.021)

Table 4: Continued

Correlated random effects (CRE)	Yes		Yes	
Instrument variables				
Log (mean rainfall in mm in last ten years)			-0.298***	(0.046)
Any cultivated land with clay loam soil? (yes = 1)			0.045**	(0.021)
Any cultivated land with very high elevation? (yes = 1)			-0.039**	(0.020)
/athrho	-0.528**	(0.269)		
rho	-0.487	(0.206)		
Wald test of rho = 0: chi2(1)		3.83**		
Murphy's score test for biprobit chi2(9) =		6.01 (*p*-val = 0.74)		
Average treatment effects (ATE)	0.33***	(0.099)		
Average treatment effects on the treated (ATT)	0.31***	(0.089)		
Observations		1691		

Both the BPM and the SPM rely on normality assumptions. The SPM, however, has two main advantages over the BPM: it relaxes the assumption of equality of coefficients of the non-farm participation equations in two regimes, and it is therefore more efficient than the BPM. Regime-specific coefficients allow us to observe the relative role of explanatory variables in two different regimes. The differences between the coefficients of two regimes are noteworthy. Most covariates appear statistically insignificant in explaining the participation of households in the non-farm sector. Only a higher dependency ratio, represented by the household size, could induce households that do not adopt labor-saving technology to participate in the non-farm sector.

The SPM is implemented using Stata's switch_probit module, developed by Lokshin and Sajaia (2011), and the results from the SPM are reported in Table 5. The Wald test for independent equations was weakly rejected, and the joint maximum likelihood estimation of the participation equation and the technology adoption equation is valid. The significant negative value of rho1 implies that the unobservable that affects households' technology

adoption decision is negatively associated with the unobservable that affects households' participation in the non-farm sector. Therefore, estimating a simple probit model to estimate the non-farm participation effects of technology adoption would lead us to biased and inconsistent results, and thus the use of SPM is a valid approach.

In the selection equation, the instruments appeared to be statistically significant. While the rainfall and the land elevation reduce the probability that a power tiller or tractor will be adopted for land preparation, land with clay loam soil increases the likelihood that farm households will adopt technology in agricultural production. Land fragmentation also increases the probability of the adoption of labor-saving technology, because scattered land holdings require more family labor time for land preparation and might thus induce farm households to use rented power tillers or tractors to offset the increased land preparation time. In the relevant literature, it is often argued that farm operators' education helps in quick agricultural technology adoption, but this study's results indicate that the schooling of working members is not an important driver of technology adoption in rural farm households. Similarly, although it is often argued that large farm households are more inclined to adopt the modern agricultural technology, the size of the landholding also appears statistically insignificant as a driver of technology adoption.

Overall the non-farm participation effects of households' observable characteristics—particularly land endowment, human capital endowment and connectivity status—varies significantly across regimes. Having a large family size boosts non-farm participation more for households that do not adopt mechanized land preparation than for households that have mechanized land preparation. On the other hand, having an extra worker in the family leads

technology-adopting households to participate more in the non-farm sector than it does in farm households that do not adopt mechanized land preparation in farming. Female participation in the labor force induces the non-mechanized households to participate more in the non-farm sector than the mechanized households, although it appears statistically insignificant in both regimes. Both educational level and NGO membership matter for the non-farm participation of farm households with technology adoption; a 1% increase in human capital assets of agricultural households increases their probability of involvement in the non-farm sector by 3.3%, while NGO membership of farm households increases the likelihood by 36%. Land fragmentation also differently influences the non-farm participation decision in households that do and do not adopt the labor-saving technology. For the adopting farm households, doubling the land fragmentation index reduces the likelihood of non-farm participation by 38%. Small, medium, and large landowner households, irrespective of whether they do or do not use power tillers and/or tractors, participate in the non-farm sector equally with the marginal landowner households.

Overall, the ATE slightly decreased, from 0.33 in the BPM to 0.31 in the SPM. The ATEs from both the SPM and the BPM differs much from the ATE from instrumental variable regression (IVREG). This difference is expected, because the linear probability instrumental variable regression performs poorly when it is applied to estimation of binary choice models with binary endogenous covariates, especially in cases of extreme probabilities of participation in the selection groups; in the analysis here, the proportion of households with non-farm participation is 0.49, and the proportion of households with mechanization is 0.88 (Altonji, Elder, & Taber, 2005).

Table 5 :Endogenous Switching Probit Estimates

	Endogenous switching probit model					
	Mechanized households		**Non-mechanized households**		**Mechanization equation**	
	Coeff.	***SE***	**Coeff.**	***SE***	**Coeff.**	***SE***
Age of household head	0.003	(0.007)	-0.018	(0.013)	-0.003	(0.006)
Household size	0.033	(0.025)	0.155**	(0.064)	0.027	(0.025)
Labor endowment dummies (ref: single working member)						
Two adult workers	0.253**	(0.108)	0.147	(0.203)	-0.176	(0.120)
Three adult workers	0.421**	(0.178)	-0.062	(0.331)	-0.162	(0.183)
Female participation in labor force (yes = 1)	0.170	(0.153)	0.575	(0.355)	0.052	(0.158)
Log (total schooling years of workers)	0.033*	(0.019)	0.041	(0.042)	-0.024	(0.021)
Land endowment dummies (ref: marginal landowner (<0.4 Ha))						
Small landowner (> = 0.4 Ha & <1.0 Ha)	-0.019	(0.115)	-0.105	(0.216)	0.113	(0.125)
Medium landowner (> = 1.0 Ha & <2.0 Ha)	0.052	(0.158)	-0.005	(0.264)	0.057	(0.150)
Large landowner (> = 2.0 Ha)	0.296	(0.221)	0.372	(0.410)	0.294	(0.208)
NGO membership (yes = 1)	0.355***	(0.083)	0.179	(0.149)	-0.044	(0.091)
Log (gross margin of farming in 2008 Tk.)	0.004	(0.039)	-0.005	(0.094)	-0.008	(0.043)
Fragmentation Index	-0.384*	(0.233)	-0.047	(0.400)	0.390*	(0.225)
Cropping intensity	0.037	(0.109)	0.020	(0.244)	0.082	(0.132)
Year dummy (2008 = 1)	-0.426***	(0.117)	-0.481	(0.309)	0.898***	(0.079)
Correlated effects variables (group means of the variables)			Yes			
Instrument variables						
Log (mean rainfall in mm in last ten years)					-1.157***	(0.204)
Any cultivated land with clay loam soil? (yes = 1)					0.170*	(0.090)
Any cultivated land with very high elevation? (yes = 1)					-0.152*	(0.084)
Constant	0.702*	(0.389)	0.107	(0.604)	7.984***	(1.533)
/athrho1	-0.575	(2.409)				
/athrho0	-0.490	(3.590)				
rho1	-0.52	(1.76)				
rho0	-0.45	(2.85)				
Wald test if indep. eqns. (rho1 = rho2 = 0) Chi2			4.8* (*p*-val = 0.09)			
Observations	1691					
Average treatment effects (ATE)	0.31					
Average treatment effects on the treated (ATT)	0.28					
Wald chi2(23)	241.55***					
Observations	1691					

Note. Standard errors are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

1.5.2. Labor Supply Equations

This subsection presents results for the labor supply equations. Table 6 presents results from the IV estimation; the results from the ETE model are shown in Table 7. Although the use of the IV approach is inappropriate in the case of an endogenous dummy regressor, as previously discussed, IV regression has been estimated to get the test statistics that extensively examine the validity of the instruments. Like the participation equation, the endogeneity of the technology adoption decision needs to be checked, and both the Durbin's score statistics and the Wu-Hausman tests reject the null hypothesis that the technology adoption decisions of farm households are exogenous to their non-farm labor supply decisions. All three instruments pass Sargan's orthogonality tests; the test statistics fail to reject the null hypothesis of orthogonality of instruments to the non-farm labor supply decision. Besides their orthogonality to the outcome variable, the instruments are well correlated with the endogenous regressor, as the null hypothesis of the instrument's redundancy has, for each instrument in LR IV, been rejected. The model also passes all the necessary tests (e.g. underidentification, weak identification, overidentification) for validity of the instruments. All the relevant tests (Hausman, Wu-Hausman, Durbin's score) for endogeneity confirm the presence of endogeneity between the non-farm participation decision and the technology adoption decision of a farm household. The F-stat at the first-stage regression also passes the "more than 10" rule, indicating that the excluded instruments are valid and significantly relevant. The instruments also pass the Montiel-Pflueger robust weak instrument test; the effective F statistic at 5% confidence level (19.77) is well above the generalized TSLS critical value at 5% worst-case bias (13.42). Thus, the use of rainfall, soil quality, and land elevation as instruments

predicting the likelihood of adoption of power tiller or tractor in land preparation does not suffer from the usual weak instrument problems. Both the Wald test and the Smith-Blundell test for exogeneity reject the null hypothesis of exogeneity of the technology adoption decision.

Although the explanatory variables in the outcome equation are mostly statistically insignificant in the first-stage regression of determining the technology adoption decision, all the instruments appear statistically significant. One percent more rainfall reduces the probability of technology adoption of a farm household by 0.32. Farm households that operate land with clay loam soil are not significantly different in adopting mechanized tillage systems than farm households that do not operate land with clay loam soil. As before, farm households that operate land with high elevation are 6% less likely to adopt labor-saving technology than farm households that do not have land with high elevation.

Table 6: IV Model Estimates of Labor Supply of Farm Households

Dep. Var.: Number of Workdays in Non-Farm Sector in previous 12 months	Instrumental variable (IV) 2SLS model			
	Non-farm labor supply equation		Mechanization equation	
	Coeff.	*SE*	Coeff.	*SE*
Mechanized (yes = 1)	126.620**	(53.896)		
Age of household head	-0.210	(0.741)	-0.001	(0.002)
Household size	2.886	(2.868)	0.008	(0.007)
Labor endowment dummies (ref: single working member)				
Two adult workers	41.497***	(12.710)	-0.049	(0.030)
Three adult workers	92.398***	(20.187)	-0.051	(0.048)
Female participation in labor force (yes = 1)	21.803	(16.868)	0.006	(0.041)
Log (total schooling years of workers)	4.337*	(2.354)	-0.006	(0.006)
Land endowment dummies (ref: marginal landowner (<0.4 Ha))				
Small landowner (> = 0.4 Ha & <1.0 Ha)	-1.534	(12.577)	0.025	(0.030)
Medium landowner (> = 1.0 Ha & <2.0 Ha)	-4.406	(16.387)	0.007	(0.039)
Large landowner (> = 2.0 Ha)	23.843	(22.428)	0.062	(0.054)
NGO membership (yes = 1)	31.943***	(8.821)	-0.014	(0.022)
Log (gross margin of farming in 2008 Tk.)	0.551	(4.910)	-0.004	(0.012)
Fragmentation index	-71.543***	(26.159)	0.119*	(0.061)
Cropping intensity	-1.518	(13.723)	0.005	(0.033)
Year dummy (2008 = 1)	-27.371*	(16.250)	0.244***	(0.022)
Correlated effects variables (group means of the variables)		Yes		
Instrument variables				
Log (mean rainfall in mm in last ten years)			-0.318***	(0.049)

Table 6: Continued

Any cultivated land with clay loam soil? (yes = 1)			0.032	(0.022)
Any cultivated land with very high elevation? (yes = 1)			-0.058***	(0.020)
Constant	45.664	(40.082)	2.734***	(0.368)
Wald chi2(21)	278.3***			
F(23, 1667)			10.40***	
R-squared	0.093		0.122	
Observations	1691			
Underidentification tests (Ho: Model is underidentified) Anderson canon. corr. likelihood ratio stat Chi-sq(3) = 58.2 (p = 0.000)				
Weak identification statistics: (Ho: Instruments are weak) Montiel-Pflueger robust weak instrument test: Effective F statistic: 19.77**				
Partial *R*-squared of excluded instruments: 0.0344 Test of excluded instruments: F(3, 1667) = 19.77 (p = 0.000)				
Sargan (score) test of overidentifying restrictions chi2(2) = 2.95 (p = 0.23)				
Tests of endogeneity: (H0: mechanization is exogenous) Durbin (score) chi2(1) = 4.02(p = 0.04); Wu-Hausman F(1,1668) = 3.97 (p = 0.04)				
LR IV redundancy tests for instruments: (Ho: Instrument is redundant) Rainfall: Chi-sq(1) = 41.5***; Soil Quality: Chi-sq(1) = 2.85*; and Land elevation: Chi-sq(1) = 8.2***				
Sargan's orthogonality tests for instruments: (Ho: Instrument is orthogonal to the outcome variable) Rainfall: Chi-sq(1) = 0.17; Soil Quality: Chi-sq(1) = 2.5; and Land elevation: Chi-sq(1) = 0.73				
IV heteroscedasticity test(s) using levels of Ivs only: (Ho: Disturbance is homoscedastic) Pagan-Hall general test statistic: Chi-sq(23) = 65.7 (p = 0.00)				

Note Standard errors are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7 presents results from the ETE estimation for the level of off-farm labor supply. As seen in the participation decision, the technology adoption dummy appears statistically significant, with the expected sign. Adoption of labor-saving technology in land preparation results in 64 days of extra labor supply in off-farm work.

In addition to the technology adoption decisions, the estimation controls as before for other household characteristics, such as demography, physical assets, and human capital assets. Demographic characteristics appear as important drivers of the off-farm labor supply decisions of farm households. Both the household size and the number of adult working members increase farm households' off-farm labor supply hours. Female participation in the workforce also induces farm households to supply more labor hours in the non-farm sector. Surprisingly, land ownership (with the exception of large landowner households) and gross margin (returns

from cultivable landholding and family labor) appear to be statistically insignificant. Land fragmentation also appears statistically insignificant, though its sign is expectedly negative. NGO membership, as expected, induces farm households to supply extra labor hours in the non-farm sector and appears statistically significant with a positive sign.

The dummy for the year 2008 appears statistically significant with a negative sign, implying that farm households supplied less labor in the non-farm sector in 2008 than they did in 2000. This result is not surprising, because the return from agricultural production increased significantly in 2008 due to a surge in global food prices in the late 2000s. It is evident that the growth of farm income contributed 90% of poverty reduction in the second half of the last decade in Bangladesh (World Bank, 2013). Workers' schooling does not have a significant effect on farm households' off-farm labor supply, a result that is consistent with the earlier literature (see Sumner, 1982; Mishra & Goodwin, 1997).

Table 7: Endogenous Treatment Effects Model

	Endogenous treatment effects model			
Log (non-farm workdays)	**Non-farm labor supply equation**		**Mechanization equation**	
	Coeff.	***SE***	**Coeff.**	***SE***
Mechanized (yes = 1)	64.140**	(30.845)		
Age of household head	-0.264	(0.797)	-0.004	(0.007)
Household size	3.411	(2.956)	0.031	(0.025)
Labor endowment dummies (ref: single working member)				
Two adult workers	38.842***	(12.800)	-0.174	(0.115)
Three adult workers	89.438***	(22.100)	-0.160	(0.183)
Female participation in labor force (yes = 1)	22.062	(18.821)	0.056	(0.150)
Log (total schooling years of workers)	3.926**	(1.947)	-0.023	(0.022)
Land endowment dummies (ref: marginal landowner (<0.4 Ha))				
Small landowner (> = 0.4 Ha & <1.0 Ha)	-0.350	(11.957)	0.117	(0.115)
Medium landowner (> = 1.0 Ha & <2.0 Ha)	-4.668	(15.860)	0.068	(0.146)
Large landowner (> = 2.0 Ha)	26.418	(24.290)	0.301	(0.207)
NGO membership (yes = 1)	32.272***	(8.458)	-0.054	(0.083)
Log (gross margin of farming in 2008 Tk.)	0.173	(4.774)	-0.003	(0.046)
Fragmentation index	-64.144***	(23.866)	0.405*	(0.245)

Table 7: Continued

Cropping intensity	-0.709	(12.728)	0.065	(0.131)
Year dummy (2008 = 1)	-11.620	(10.809)	0.905***	(0.087)
Correlated effects variables (group means of the variables)		Yes		
Instrument variables				
Log (mean rainfall in mm in last ten years)			-1.176***	(0.184)
Any cultivated land with clay loam soil? (yes = 1)			0.142*	(0.084)
Any cultivated land with very high elevation? (yes = 1)			-0.158**	(0.077)
Constant	70.886**	(34.452)	8.118***	(1.384)
Log pseudo-likelihood	-11737			
Observations	1691			
/athrho	-0.16	(0.11)		
/lnsigma	5.06***	(0.025)		
rho	0.15	(0.10)		
sigma	158.3	(3.69)		
lambda	-24.36	(16.6)		
Wald test of indep. eqns. (rho = 0): chi2(1) =	1.03 (*p*-val = 0.31)			

The robustness of the results has been checked by excluding the top 10% of households supplying off-farm labor in the ETE model; the results of this exclusion are presented in Table A5 in the Appendix. The results show that a household's adoption of labor-saving technology has a significant and substantial effect on how much off-farm labor it supplies. The farm households that have mechanized land preparation for farm production supply 57 more days of off-farm work. Therefore, the labor supply effects of the technology adoption presented in Table 7 are robust and reliable.

1.6. Concluding Remarks

This paper examines the role of agricultural mechanization (through the adoption of labor-saving technology, namely tractors and/or power tillers) in the off-farm labor supply decisions of farm households using longitudinal household survey data from Bangladesh. The study uses the BPM, the endogenous SPM, and the ETE models to identify whether the

adoption of modern technology in land preparation affects how much off-farm labor farm households supply. The results confirm that a farm household's adoption of modern technology in farm production could raise both the farm household's probability of participation in the non-farm sector and the number of hours worked in the non-farm sector. Also, this paper also finds that land fragmentation could reduce both a farm household's participation in off-farm works and the number of hours worked in the non-farm sector; receipt of microcredit, however, induces farm households to participate in the non-farm sector and to work more in the non-farm sector.

The results have important policy implications for developing countries like Bangladesh, where the farm sector is the dominant sector for productive employment. Because non-farm employments are generally more productive and remunerative than farm employment, farm mechanization could benefit farm households by inducing them to supply more labor to the non-farm sector. Developing economies that experience high growth in the non-agricultural sector could promote agricultural mechanization by promoting private-sector supply of mechanized agricultural equipment. Private initiatives in equipment research and development could also promote agricultural mechanization; given the proper economic conditions, the private sector has historically been an efficient provider of equipment and mechanization services (Pingali, 2007).

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CHAPTER 2: COPULA-BASED MODELING OF DEPENDENCE STRUCTURE AMONG GLOBAL FOOD GRAIN MARKETS

2.1. Introduction

The stability of global food grain markets is one of the major policy concerns for policy-makers and analysts around the world, especially those from net food-importing developing countries, where food grain costs are high in relation to income, adversely affecting the poor. The welfare implications of food price instability are enormous; the sharp food price hike of the late 2000s adversely affected poor people in poor countries across Africa and Asia (Dorosh, Dradri, & Haggblade, 2009; Hernandez, Robles, & Torero, 2011). The large increase in food prices between 2005 and 2007 drove about 155 million people around the world into poverty, increasing the global population in extreme poverty by 1.7% (De Hoyos & Medvedev, 2011). Tokgoz, Wailes, and Chavez (2011) also showed that the countries that were most adversely affected by the price hikes of the 2000s were poor food-deficit and net food-importing countries. A sudden price surge in international markets also destabilizes the macroeconomic management of net food-importing countries, because the account deficits of these countries soar during periods of high food prices in international markets.

There have been published many studies and reports investigating the drivers behind the commodity price boom in global markets in the late 2000s. Piesse and Thirtle (2009) and Carter, Rausser, and Smith (2011) surveyed the relevant literature and found three prominent causes for the global food price hike of the 2000s. These three top drivers are: (a) speculation, which, along with arbitrage activities in commodity futures markets, played an important role in the global commodity price boom (see Cooke & Robles, 2009; Tadesse, Algieri, Kalkuhl, & von Braun, 2014); (b) a supply shock, caused by export restrictions or politically motivated

export bans with embargoes, which caused global commodity prices to skyrocket (see Slayton, 2009; Headey, 2011; Tokgoz et al., 2011; Anderson, 2012; Rude & An, 2015); and (c) a demand shock to the U.S. corn market as a result of the 2007 change to the U.S. biofuel policy, which increased the use of corn for ethanol production, raising the global demand for corn significantly and causing the sharp rise in world commodity prices (see Mitchell, 2008; Chen, Kuo, & Chen, 2010; Roberts & Schlenker, 2010; Chakravorty, Hubert, Moreaux, & Nøstbakken, 2012).

Speculation and arbitrage activities in commodity markets have recently increased because of futures markets trading in commodity exchange markets. Futures attract investors who may not be interested in the commodity but who hope to make speculative profit on future movements in the price of the commodity. Commodity futures have become increasingly attractive to noncommercial investors, as their returns seem negatively correlated with returns on equities and bonds. Commodity futures thus constitute an attractive vehicle for portfolio diversification. According to the Food and Agriculture Organization (FAO), there has been a significant inflow of funds from traditional institutions, such as hedge funds and pension funds, and newer commodity-linked and exchange-traded funds into agricultural commodity futures markets (FAO, 2011). Speculative activities in the commodity futures markets raise the volume of futures trading, which causes a subsequent increase in futures prices of commodities. The increase in futures prices in turn raises spot commodity prices. Speculation could thus have played a role in commodity price hike in the 2000s. The role of speculation in commodity price hikes remains inconclusive in the relevant literature, however; although empirical evidence in Robles, Torero, and Braun (2009) implies that the "speculative bubble hypothesis" may be explanatory, many other studies argue against speculation playing an important role in food

price hikes (Irwin, Sanders, & Merrin, 2009; Wright, 2011). Tadesse et al. (2014) find that financial speculation contributes to short-term commodity price volatility.

Another key factor behind the commodity price boom in the late 2000s was the introduction of deliberate restrictions on agricultural exports, such as export bans and raising or introducing export taxes (see Mitchell, 2008; Jones & Kwiecinski, 2010; Headey, 2011; Martin & Anderson, 2012; Anderson & Nelgen, 2012; Rude & An, 2015). According to the International Monetary Fund (IMF), at least 30 countries around the world imposed some forms of export restriction during that price boom (IMF, 2008). For example, Argentina raised export taxes on soybeans from 35% to 45%; India banned exports of wheat and non-basmati rice; Vietnam restricted rice exports; and Kazakhstan banned wheat exports. Martin and Anderson (2012) estimate that approximately 30% of rice price increases and 25% of wheat price increases in the period of 2005–2008 were due to the export control measures of exporting countries. Anderson and Nelgen (2012), who examine the government responses to sudden exogenous price spikes and the domestic price stabilization effects of those interventions in 75 countries, show that government responses to price spikes weakened the domestic price stabilizing effect of their interventions and thus exacerbated those shocks.

Mitchell (2008) argues that global rice markets experienced a steady increase in prices following the exports bans, particularly India's export ban, as the price expectations of remaining rice exporters such as Thailand increased. Rude and An (2015) examine the global price volatility effects of export restrictions and, using a univariate structural time-series approach, conclude that export restrictions implemented over the period of 2006–2011 contributed significantly to the rice and wheat price volatilities, but did not substantially

contribute to corn and soybean price volatilities. Tokgoz et al. (2011) find that trade policy distortions contributed 24% of the total price increase in international markets. Headey (2011) suggests that trade events were pervasively important in all of the major food grain markets and argues that the trade events provide the most tangible explanation for the overshooting of global food prices.

The most common and most universally agreed-upon explanation of the commodity price boom is that it was mainly driven by a demand shock in the U.S. corn market caused by a 2007 shift in the U.S. ethanol production policy. Mandatory blending policies adopted by the United States and the European Union (EU) regarding biofuel production greatly increased the use of corn in biofuel production. Thus, many studies have found that biofuel and energy mandates can have a large impact on global food prices (Mitchell, 2008; Chen et al., 2010; Chakravorty et al., 2011). Roberts and Schlenker (2010) claim that 30% of the rise in the average price of staple food commodities was driven by excess biofuel demand in 2007–2008. Mitchell (2008) also argues that the excess demand for corn caused by the production of ethanol in the United States was the single ultimate cause of the commodity price increase. Mitchell (2008) reports that biofuel use of corn has increased by 50 million tons in the United States over the period 2004–2007; the global production of corn increased by only 55 million tons in the same period. Abbot, Hurt, and Tyner (2011) argue that biofuels policy has brought about a significant, persistent, and non-price-responsive demand for corn.

Studies of the rice market price boom in the 2000s argue that biofuel policy change played an even larger role in this price boom (FAO, 2008). The economics of substitution in supply and demand created strong linkages among food grain markets, and other food grain

markets responded to the demand shock in corn markets that came from ethanol production policy changes. Supply substitutability led to higher corn production and lower wheat and soybean production in the United States, while demand substitutability transmitted corn market shocks into other food grain markets. Mitchell (2008) also presents evidence of land substitution between corn, soybeans, and wheat, suggesting a possible comovement of grain prices. More than 30% of corn produced in 2008 was used for ethanol production; the comparable figure was only 14% in 2005. This diversion of food crops to energy drives food prices significantly: first, through the direct effect on corn prices, and second, through the economics of substitution with other commodities—the United States is responsible for around 40% of global corn production and accounts for more than 60% of the world corn exports. It is, however, not known how perfect the price transmission is among these grain prices (Piesse and Thirtle, 2009). The FAO (2008) argues that the global demand for corn increased by 40% in 2007, and that 75% of this increase was from ethanol production. The demand shock in corn due to ethanol policy both lowered acreage of wheat and soybeans and significantly reduced corn inventory levels.

Some other arguments have also been proposed to explain the sudden price hike, including depreciation of the U.S. Dollar, poor harvests, low interest rates, and economic growth. Piesse and Thirtle (2009) do not find consensus on the impact of the depreciation of the U.S. Dollar on the global commodity price surge, although Roache (2010) concludes that the variation in U.S. inflation and the U.S. Dollar exchange rate explains a relatively large part of the rise in food price volatility since the mid-1990s.

Overall, the literature on the causes of the global food price hike and extreme volatility highlights three factors as a major driving force of the global price surge. One strand of literature presents trade restrictions and agricultural trade policies as the most tangible explanation for the spike in global commodity prices (Headey, 2011; Anderson, 2012). Another strand of literature argues that the United States' excess demand for corn to produce ethanol was the single strongest cause of the commodity price increase (Mitchell, 2008). The third strand of literature on the global commodity price hike concludes that financial speculation in the futures market explains the majority of the change in food prices (Cooke & Robles, 2009).

Against this backdrop, the question that remains unaddressed in relevant literature is the following: What is the extent of integration or dependence among global food grain markets that allowed shocks in one market to be so rapidly transmitted to other markets? Why should the changes in biofuel policy mandates in the United States and speculation in the futures commodity markets affect the Thai-centered global rice markets? Why should the trade restriction decisions on Asian rice markets, imposed by the Vietnamese and Indian governments, affect the food prices in the United States? The dependence structure among global food grain markets is what determines the speed of shock transmission from one market to another, and the policy-makers and analysts concerned with food price stabilization should have a clear understanding of these dependence structures in order to formulate and implement proper policy tools in times of food price volatility. Efficient trade and arbitrage activities should ensure that prices of related goods in major food markets are well integrated through a common long-run equilibrium.

The relevant literature, however, does not currently devote much attention to the dependence structure between spatially separated global food grain markets, and studies on dependence structure among major global financial markets using copulas (the proper analytical tool for the job) are especially rare. While stock markets are more dependent on the state of "crush" than "boom," global food grain markets seem more dependent on up days than down days. As price elasticity for a staple food is usually low, overall food prices are expected to respond little to a large price change for a specific cereal. A large price change of a specific grain, however, could generate panicked responses from agents involved in the food grain markets due to the economics of substitutions in supply and demand.

Because of its social and political relevance, the connections between agricultural commodity markets have received considerable attention since the late 2000s. While correlations among price changes of food grains are historically quite low, many studies in the relevant literature argue that increasing linkages among food, energy, and financial markets explain much of the overserved food price spikes and volatility (Tadesse et al., 2014). Despite the fact that studies on comovement of prices for food grains are somewhat limited, there are numerous studies on the notions of price parity, price transmission, and price arbitrage relationships for tradable homogeneous goods. The main idea of those studies is that efficient functioning of the market should ensure stable links across spatially separated regional markets and should eliminate any potential for persistent spatial arbitrage profits. This fundamental condition is known as the "Law of One Price" (LOP), and its general implication is that prices in spatially separated markets should vary by no more than the transport and transaction costs. There is a long history of empirical models of price linkages, and models have ranged from simple price correlation tests to conventional regression analysis to the current time-series

models, which account for nonstationarity, nonlinearities, and threshold behavior in market linkages.

Empirical support for LOP is rather mixed. While early studies (see Isard, 1977; Thursby, Johnson, & Grennes, 1986; and Benninga & Protopapadakis, 1988) fail to find support for the LOP, Goodwin, Grennes, and Wohlgenant (1990) do, however, find some evidence for the LOP when the LOP is specified in terms of price expectations instead of observed prices. Cointegration techniques have been widely used to evaluate the LOP as a long-run concept, following the seminal paper by Engle and Granger (1987), establishing more compelling evidence for the LOP (see Buongiorno & Uusivuori, 1992; Bessler & Fuller, 1993; and Jung & Doroodian, 1994). The most recent literature in this area applies smooth or discrete threshold time-series models that have the underlying assumption that the corrections to equilibrium may not be linear, and that this nonlinearity may, in turn, be linked with hard-to-observe transaction costs related to arbitrage. Studies find that nonlinearity is an important feature of price relationships in agricultural commodity markets and that the price parity relationships implied by the economic theory and efficient arbitrage are generally supported by the threshold models (see Holt, Prestemon, & Goodwin, 2011; Goodwin & Piggott, 2001; Lo & Zivot, 2001; Sephton, 2003; Balcombe, Bailey, & Brooks, 2007; and Park, Mjelde, & Bessler, 2007). Very recently, researchers have started to use the copula in modeling spatial price linkages. Goodwin et al. (2011) estimate copula-based nonlinear models for pairs of North American Orient strand board (OSB) prices and find even stronger evidence of nonlinearities in spatial market linkages.

These studies have generally examined the notions of price parity, price transmission, and arbitrage activities for a tradable homogeneous good. However, studies on price transmission and price linkages among the international food grain markets are limited. The understanding of commodity prices and their forecasting ability remains extremely limited (Deaton, 1999), and this insufficient understanding makes it difficult to construct good policy rules. This chapter focuses on improving the understanding of the dependence structure among global food grain markets and hence advances the ability to forecast food grain prices. This chapter examines the link between global food grain markets and proposes an alternative, novel approach: the use of copula models to analyze the dependence structure among global food grain markets. The copula-based models consider the joint distribution of prices from different markets and apply them to weekly prices for food grains in geographically distinct global markets. To improve the ability to create precise forecasts of food grain prices in the future, a careful examination of the dependence structure among food grain markets is needed. Evaluation of this dependence structure among markets could serve two purposes: as a risk-management tool, allowing speculators operating in the commodity exchange markets to forecast future price movements, and as an improved forecasting tool for policy-makers around the world who create policies to ensure food security.

We have seen an influx of applications of copula models in finance recently, and these models have been recognized to be a very suitable tool for modeling the dependence structure among financial markets. Like financial markets, international food grain prices tend to exhibit asymmetric dependence. This asymmetry implies that in times of upward trend, prices tend to be more dependent than they are in periods of downward trend. This trend has important implications for risk: that of speculators and arbitragers who operate in commodity futures

markets, and that of policy-makers who formulate policy to ensure food security. The copula models differ regarding how the dependencies among variables are presented. For example, a Gaussian copula assumes linearity in correlation and imposes zero dependence at the distribution's tails. The *t* copula allows for non-zero dependence at the tails but imposes symmetry in the dependence relationships in other tails of the distributions. Archimedean copulas typically permit dependence in only one tail and represent the dependence relationship by using a single parameter. Thus, the choice of copula function governs the nature of the relationships between dependent random variables (see Figure 2 and Figure 3).

This chapter applies the copula models to study the comovement and the tail dependence of food grain prices using the three most traded food grains in the global food grain markets: rice, wheat, and corn. The approach this chapter uses is a natural extension of the existing time-series evaluations of spatial price linkages. The contribution of this paper in the relevant literature is twofold. First, the chapter examines the dependence structure among global food grain markets to remedy the lack of studies that explore the integration among these markets. Second, the chapter models this dependence structure using copulas, which allow modeling in a much more flexible and realistic way than earlier models based on the Gaussian distribution. The use of copulas makes it possible to separate the dependence model from the marginal distributions. The copulas also allow having tail dependence, which means that, unlike with Gaussian distribution, the dependence does not vanish with increasingly upward price changes. Moreover, the research, which applies copulas in the multivariate context of food market integration, employs both a canonical vine (C-Vine) and a D-vine copula, which allow for realistic applications of very general types of dependence.

The remainder of the chapter is organized as follows. Following the introductory discussion in Section 2.1, discussion on methodology and models are presented in Section 2.2, which discusses the two-step estimation procedures of the model, the method of copulas, and the method of the general autoregressive conditional heteroskedasticity (GARCH) model that is used for modeling the marginals. Section 2.3 presents a discussion on data sources and summary statistics of the price series, which is useful in describing the data and making initial decisions about the selection of the appropriate copula and GARCH process. In Section 2.4, the results and discussions of GARCH models for the marginal and the results of the copula models are presented. The chapter ends with concluding remarks in Section 2.5.

2.2. Specifications and Methodology

In the 2000s, copula modeling became a frequently used tool in financial economics.[10] This chapter adopts an empirical modeling approach that uses copulas to model price changes using the joint distribution function of $\Delta(p_t^i - p_{t-1}^i)$ and $\Delta(p_t^j - p_{t-1}^j)$. The fundamentals of copulas date to work by Sklar (1959). Sklar's (1959) theorem implies that any joint probability function can be represented in terms of the marginal densities and a function known as a copula.

2.2.1. Copulas

A p-dimensional copula, $C(u_1, u_{2,} \dots \dots, u_p)$, is a multivariate distribution function in the unit hypercube $[0, 1]^p$ with uniform U (0, 1) marginal distributions. Sklar (1959) has

[10] A detailed review of copula theory is available in Joe (1997) and Nelsen (2006).

demonstrated that, as long as the marginal distributions are continuous, a unique copula is associated with the joint distribution, F, that can be obtained as follows:

$$C\left(u_1, u_{2,} \dots \dots, u_p\right) = F(F_1^{-1}(u_1), F_2^{-1}(u_2), \dots \dots \dots \dots \dots, F_p^{-1}(u_p)) \qquad (2.1)$$

In a similar fashion, given a p-dimensional copula, $C\left(u_1, u_{2,} \dots \dots, u_p\right)$, and p univariate distributions, $F_1(x_1), F_2(x_{21}), \dots \dots \dots \dots, F_p\left(x_p\right)$, then equation (2.1) is a p-variate distribution function with marginal $F_1, F_2, \dots \dots, F_p$ whose corresponding density function can be written as

$$f\left(x_1, x_2, \dots \dots \dots \dots, x_p\right) = c(F_1(x_1), F_2(x_{21}), \dots \dots \dots \dots, F_p\left(x_p\right)) \prod_{i=1}^{p} f_i(x_i) \quad (2.2)$$

Provided that the copula exists, the density function of the copula, c, can be derived based on equation (1) and marginal density functions, f_i, as follows:

$$c\left(u_1, u_2, \dots \dots, u_p\right) = \frac{f(F_1^{-1}(u_1), F_2^{-1}(u_2), \dots \dots \dots \dots \dots, F_p^{-1}(u_p))}{\prod_{i=1}^{p} f_i(F_i^{-1}(u_i))}$$

There are at least three properties exhibited by multivariate data structure that cannot be modeled with standard parametric distributions such as the Gaussian or multivariate *t* distributions; these properties are different marginal distributions, non-symmetric dependencies between some pairs of prices, and heavy tail dependencies between some pairs of prices. Though the copula approach allows for modeling dependencies and marginals separately, standard multivariate copulas do not allow for seperate dependency models between pairs of variables; a vine copula overcomes these shortcomings. Joe (1996) first outlined a probabilistic construction of multivariate distribution functions, based on simple

building blocks called “pair-copulas.” Bedford and Cooke (2002) organized these constructions of distributions in a graphical way called “regular vines” and gave an expression for the joint density.

Aas, Czado, Frigessi, and Bakken (2009) have shown a modeling approach for multivariate data with complex dependencies in the tails using pair-copula constructions (PCC). Pair-copulas, such as Gaussian, student *t*, Gumbel, and Clayton copulas, are basic building blocks for constructing multivariate models using the PCC. The simple structure and flexibility of the PCC make it popular in modeling complex dependencies. Berg and Aas (2009) find that PCCs are superior to the other multivariate models. Hobæk Haff, Aas, and Frigessi (2010) explore the limitations of the PCC and show that the simplified PCC offers a good approximation even when the actual model is far from fulfilling the simplifying assumptions.

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assumptions. We, therefore, implicitly assume that conditional pair-copula densities are independent of the conditioning variables in facilitating inference.

According to Joe (1996), a joint, multivariate density function for a set of k random variables can be written in factored form as

$$f(x_1, x_2, \dots\dots\dots\dots, x_k) = f_k(x_k).f(x_{k-1}|x_k).f(x_{k-2}|x_{k-1}, x_k) \dots\dots\dots f(x_1|x_2, \dots\dots, x_k) \quad (2.3)$$

This density function is unique for a particular ordering of variables. The joint density function can also be expressed using a copula function (as noted above) as

$$f(x_1, x_2, \dots\dots\dots\dots, x_k) = c_{1\dots\dots k}\big(F_1(x_1), F_2(x_2), \dots\dots\dots\dots, F_k(x_k)) \prod_{i=1}^{k} f_i(x_i)\big) \quad (2.4)$$

For the case of two random variables, this density function reduces to

$$f(x_1, x_2) = c_{12}\big(F_1(x_1), F_2(x_2)\big).f_1(x_1)f_2(x_2). \quad (2.5)$$

Thus, after necessary rearranging, a bivariate conditional density can be written as

$$f(x_1|x_2) = c_{12}\big(F_1(x_1), F_2(x_2)\big).f_1(x_1). \quad (2.6)$$

Following this rationale, Joe (1996) demonstrated that each term in equation (2.3) can be presented as the product of a pairwise copula and a conditional marginal density function:

$$f(x|v) = c_{x,v_k|v_{-k}}\big(F(x|v_{-k}), F(v_k|v_{-k})\big).f(x|v_{-k}). \quad (2.7)$$

Following Joe's (1996) observations, Aas et al. (2009) demonstrated that a multivariate density can be expressed as a product of pairwise copulas. Bedford and Cooke (2002) presented a regular vine representation that allows considerable flexibility in representing multivariate

densities using combinations of pairwise copulas. Kurowicka and Cooke (2006) proposed two special cases of vine copulas, the canonical vine (C-vine) and the D-vine. In both cases, a general multivariate density is represented using combinations of pairwise copula functions. Both cases afford a degree of flexibility and generality not typically available in the application of conventional copula functions to higher-ordered problems. It is, however, important to mention that any such representation is unique only in reference to a particular ordering of variables. For a C-vine copula, Brechmann and Czado (2013) suggest adopting the ordering that maximizes the sum of pairwise dependencies (measured by Kendall's tau) in the root node of the vine (i.e., the node with the maximum column sum in Kendall's tau matrix). For the D-vine, we follow Brechmann (2010) and choose the specification that minimizes the Hamiltonian path of the nodes.

The D-vine and C-vine copulas differ regarding the decomposition used to represent a multivariate density function as combinations of pairwise copula functions. Aas et al. (2009) suggest that a D-vine has pairwise combinations of variables in the initial level of the tree, while the C-vine relates a single variable to all others in the original level of the tree. Aas et al. (2009) note that the D-vine is most suitable when a particular ordering of variables is suggested (e.g. a time-series context). This paper considers both the C-vine and the D-vine and selects the most appropriate specification using Vuong's (1989) non-nested specification test. The estimation procedures are implemented in the statistical software R[11].

[11] The analysis of this chapter is performed in R 3.2.5 using "VineCopula", "CDVine", "copula", "vines" and "fGarch" packages.

The goal of this chapter is to empirically estimate the dependence structure of the joint distribution of log price changes among global food grain markets. The estimation strategy involves the application of the maximum likelihood estimation of asymmetric Gaussian copula, asymmetric Archimedean copula, and pairwise D-vine copula. The optimal copula functions for each conditional pair are chosen heuristically using the minimized value of the Akaike information criterion (AIC). A large variety of copula functions (29 in all) is considered for each combination. To summarize the approach, the paper first estimates models with one symmetric Gaussian copula, then estimates a copula family from a wide range of asymmetric copula models based on AIC values for bivariate analysis of 21 different price return pairs.[12] The measure of dependence structure, Kendall's tau, is estimated for both the Gaussian copula and the selected asymmetric copula family. Then, the paper moves forward with estimating the multivariate joint distributions using vine copulas. Standard errors of the vine copula (C-vine and D-vine) model parameters are estimated through the conversion of vines to the regular vine (R-vine) copula model.

[12] Because asymmetric tail dependence is one of our goals, we considered those copula families that can capture asymmetric tail dependence well; we exclude Gaussian, student *t*, and Frank copulas from consideration in this stage.

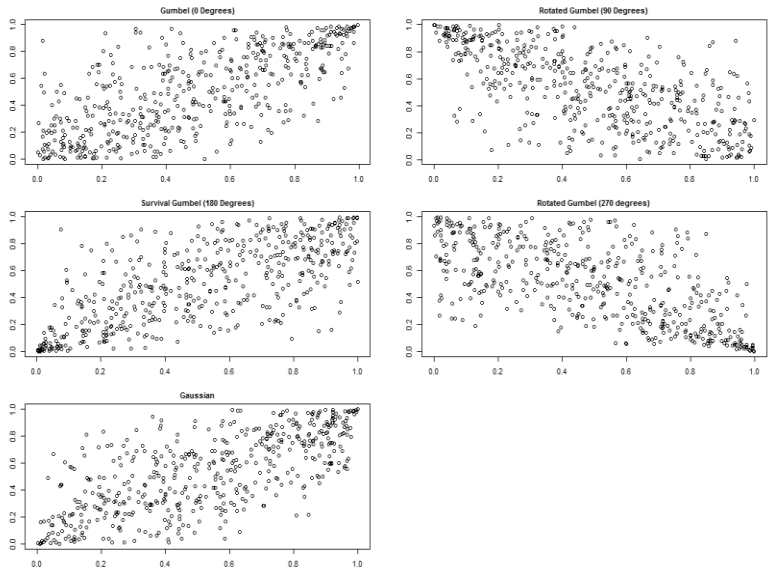

Figure 2. Scatterplots of Gumbel and Gaussian copula (simulated data, tau = 0.5, *N* = 500).

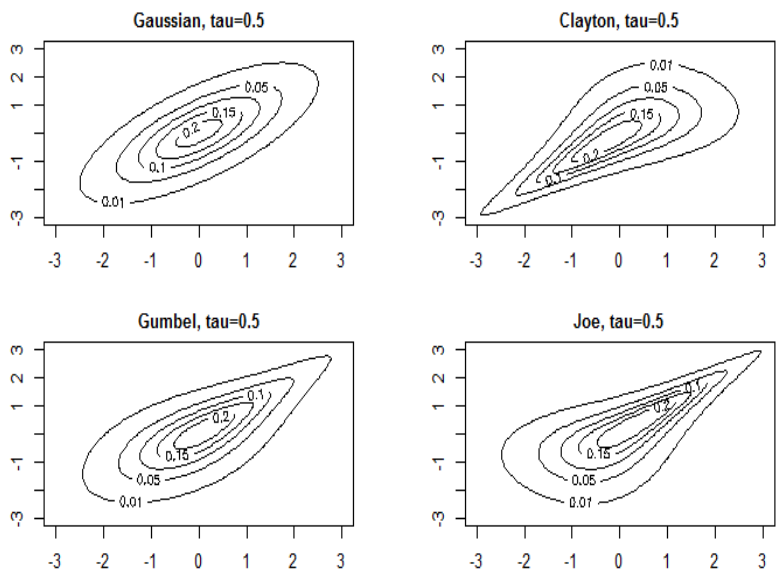

Figure 3. Contour plots of different copulas.

2.2.2. The Marginal Model: The GARCH Process

Modeling dependence structure between price returns requires finding appropriate marginal distributions for the copula model. Usually, price series observe a specific form of heteroscedasticity: today's price volatility will lead to higher volatility tomorrow. Thus, variances over time are somewhat related. This type of heteroscedasticity implies autocorrelation in squared price changes. GARCH is a model of the stochastic process that allows such type of heteroscedasticity (Engle, 2002; Bollerslev, 1986). Because GARCH is a stationary stochastic time-series process, and because the grain prices are non-stationary (augmented Dickey-Fuller [ADF)] and Phillips-Perron [PP] tests suggest so), changes in log prices have been used in the analysis, and these price returns are found to be stationary. The study uses the GARCH model instead of the ARMA-GARCH model because change price series are demeaned, which removes the autocorrelation components from the series.

Specifically, the GARCH process is expressed as follows:

$$y_t = \sqrt{h_t}.\varepsilon_t \tag{2.8}$$

Where ε_t is a white noise with $\sigma_\varepsilon^2 = var(\varepsilon_t) = 1$, and

$$h_t = \alpha_0 + \sum_{i=1}^{p} \beta_i h_{t-i} + \sum_{i=1}^{q} \alpha_i y_{t-i}^2$$

With parameters $\alpha_0, \alpha_1, \alpha_2, \dots \dots \dots \alpha_{q,} \beta_1, \beta_2, \dots \dots \dots \dots, \beta_p \geq 0$ and $\sum_{i=1}^{q} \alpha_i + \sum_{i=1}^{p} \beta_i < 1$,

ε_t accounts for 'idiosyncratic' shocks, news, etc.

Taking into consideration the characteristics of price changes in Table 8, which are non-normal and skewed, the GARCH(1,1) model with the skewed student *t* distribution is employed to capture the time-varying volatility and leverage effect, and to fit the marginal distributions for the copula model.[13] The skewed *t* distribution of Hansen (1994) has two shape parameters: a skewness parameter, which controls the degree of asymmetry, and a degrees-of-freedom parameter, which controls the thickness of the tails. Following the GARCH fit, standardized residuals are transformed into uniform distributions to plug into the copula models.

2.3. Data Source and Descriptive Statistics

To model the dependence structure among global food grain markets, the three most-traded food grains are considered: rice, wheat, and corn. To capture the dynamics within each food grain market, two or more price series for a particular food grain are used. There are quality differences in food grains, and consumers' preferences regarding grain quality vary. Substitution between food grains depends somewhat on the quality of the grain. For example, the price change of A1 Super Quality rice (a premium quality rice), which is traded in Thailand, is highly correlated with the price change of either hard wheat or soft wheat (two varieties of wheat traded in the United States); 100% Broken rice in Thailand, however, is less correlated with either type of wheat marketed in the United States. Thus, using a series for each grain would lead to a misleading conclusion about dependencies among commodity markets.

[13] I also estimated GARCH(1,1) model with normal distribution for the comparison purpose and we found that GARCH (1,1) with skewed student *t* performs better as AIC value is lowest for all marginal.

For the rice markets, three price series are used: 100% Broken in Thailand (R1), A1 Super Quality in Thailand (R2), and long grain rice in the United States (R3). For wheat, the study uses prices of Winter Hard Wheat (W1) and Winter Soft Wheat (W2) traded in U.S. export markets. For corn, U.S. corn prices (C1) and Argentine corn prices (C2) are used. Data availability determines the selection of commodities and price series. The weekly commodity price data are from the Food and Agriculture Organization (FAO) of the United Nations (UN). Price data for the period from January 2000 to December 2015 (833 observations) are used. Missing values are replaced through commonly used cubic spline interpolation.[14] The percentage of missing observations varies from 0.7 % to 6.6% of the total sample.

Table 8 presents the time-series properties of the price series. The time-series properties of the market prices are checked through the use of the augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979) and the Phillips-Perron (PP) test (Phillips & Perron, 1988). Based on the ADF test, all price series are non-stationary in levels at the conventional 5% level. The PP test also suggests that all prices are non-stationary. The first differences of all prices are, however, stationary at the conventional 5% level in both the ADF and the PP tests. As price series in levels are mostly non-stationary, and price series in first differences are stationary, we use weekly price changes. The price change (pc_t) is calculated as $pc_t = \log(p_t / p_{t-1})$, where p_t and p_{t-1} are current and one-period-lagged weekly spot prices, respectively. All price series are expressed as current U.S. Dollar per metric ton.

[14] For details of Cubic Spline intrapolation, see 'A Practical Guide to Spline' by C.De Boor, New York, Springer, 1978.

Table 8: Time-Series Properties of the Prices

Prices	Augmented Dickey-Fuller (ADF) Test		Phillips-Perron (PP) Test	
	Test Statistics	P-Value	Test Statistics	P-Value
A. Levels				
Rice (100%B, Thailand)	-1.59	0.75	-3.45	0.91
Rice (A1 Super, Thailand)	-2.30	0.45	-5.82	0.79
Rice (Long Grain, USA)	-2.49	0.37	-5.85	0.78
Wheat (Hard Wheat, USA)	-2.01	0.58	-10.06	0.55
Wheat (Soft Wheat, USA)	-2.45	0.39	-13.89	0.34
Corn (USA)	-1.85	0.64	-7.29	0.70
Corn (Argentina)	-1.50	0.79	-7.89	0.67
B. Returns				
Rice (100%B, Thailand)	-7.43	0.01	-611.92	0.01
Rice (A1 Super, Thailand)	-7.28	0.01	-696.63	0.01
Rice (Long Grain, USA)	-6.98	0.01	-766.29	0.01
Wheat (Hard Wheat, USA)	-9.19	0.01	-833.28	0.01
Wheat (Soft Wheat, USA)	-9.07	0.01	-808.12	0.01
Corn (USA)	-8.46	0.01	-880.34	0.01
Corn (Argentina)	-9.25	0.01	-838.83	0.01

Note. ADF test applies the ninth lag order, and the truncation lag parameter for the PP test was 6 for each series.

Table 9 provides descriptive statistics of the price series in return form. All price series show some positive returns and positive skewness (except rice price in the United States and corn price in Argentina). For the price of corn in Argentina, negative skewness is evident in Table 9. Positive skewness of price series indicates that the right tail of the density function of price series is fatter or longer than the left side. Thus, most price returns are right-skewed. The right-skewed nature of price returns implies that asymmetric dependence among commodity prices may be present, and price series are more dependent on each other when moving upward than when moving downward. Kurtosis values for all price series except corn price in Argentina are either well above 3 or well below 3. This fact implies that empirical distribution of price series may not be well described by the widely used normal distributions. From Figure 2.5, it is also observable that volatility in price returns is somewhat clustered, at least for rice

and corn markets; this implies that large changes in prices are followed by further large changes. From the summary statistics and plots of price returns, it is reasonable to use GARCH(1,1) with skewed student *t* distribution to model the individual marginal.

Table 9: Summary Statistics of the Price Returns (in percentages)

Variables	**Mean**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Min**	**Max**	**Observation**
Rice Price (100%B, Thailand)	0.05	2.16	2.13	21.59	-8.7	24.2	833
Rice Price (A1 Super, Thailand)	0.09	2.29	0.51	5.21	-10.9	14.8	833
Rice (Long Grain, USA)	0.07	2.10	-0.31	7.67	-12.1	10.1	833
Wheat Price (Hard Wheat, USA)	0.08	3.53	0.03	1.20	-15.3	14.5	833
Wheat Price (Soft Wheat, USA)	0.08	4.39	0.08	1.50	-16.9	21.8	833
Corn Price (USA)	0.07	3.76	0.05	2.11	-15.9	18.8	833
Corn Price (Argentina)	0.07	3.80	-0.17	3.06	-21.9	14.2	833

Note. The means are close to zero. Earlier we had means around 0.1. Because of the recent decline in food prices, average price change has declined.

Table 10 presents Spearman and Pearson's correlation coefficients for the weekly price returns; Figure 6 shows scatterplots of pairs of weekly price changes, along with correlations. It is evident, as seen in Table 10 and Figure 7, that global food grain markets are clustered according to geographic proximity. Correlations between either of the rice markets in Thailand and any other grain markets in the United States or Argentina are quite low. Even the weekly rice price changes in the United States are weakly correlated with either of the weekly rice price changes in Thailand; the highest correlation is 0.17. The elasticity of substitution between food grains is low in practice. Correlations between pairs of weekly price returns across food grains are lower than the correlations between pairs of weekly price returns for the same food grain. Even the rice market in the United States is weakly correlated with other food grains in the United States. Strong associations between wheat prices and corn prices are, however, observed, as shown in Table 10.

Table 10: Spearman and Pearson's Correlation Coefficients for the Price Changes

Variables	Rice (100%B, Thai)	Rice (A1 Super, Thai)	Rice (Long Grain, USA)	Wheat (Hard, USA)	Wheat (Soft, USA)	Corn (USA)	Corn (Argentina)
Spearman's Correlation Coefficients							
Rice (100%B, Thai)	1.00	0.54	0.12	0.01	-0.01	0.07	0.03
Rice (A1Sup, Thai)	0.54	1.00	0.04	0.08	0.06	0.10	0.06
Rice (Long Grain, USA)	0.12	0.04	1.00	0.00	-0.04	0.07	0.02
Wheat (Hard, USA)	0.01	0.08	0.00	1.00	0.79	0.46	0.44
Wheat (Soft, USA)	-0.01	0.06	-0.04	0.79	1.00	0.50	0.48
Corn (USA)	0.07	0.10	0.07	0.46	0.50	1.00	0.74
Corn (Argentina)	0.03	0.06	0.02	0.44	0.48	0.74	1.00
Pearson's Correlation Coefficients							
Rice (100%B, Thai)	1.00	0.60	0.17	-0.06	-0.03	0.04	0.01
Rice (A1Sup, Thai)	0.60	1.00	0.11	0.04	0.02	0.08	0.04
Rice (Long Grain, USA)	0.17	0.11	1.00	0.01	-0.03	0.06	0.02
Wheat (Hard, USA)	-0.06	0.04	0.01	1.00	0.80	0.49	0.45
Wheat (Soft, USA)	-0.03	0.02	-0.03	0.80	1.00	0.51	0.46
Corn (USA)	0.04	0.08	0.06	0.49	0.51	1.00	0.76
Corn (Argentina)	0.01	0.04	0.02	0.45	0.46	0.76	1.00

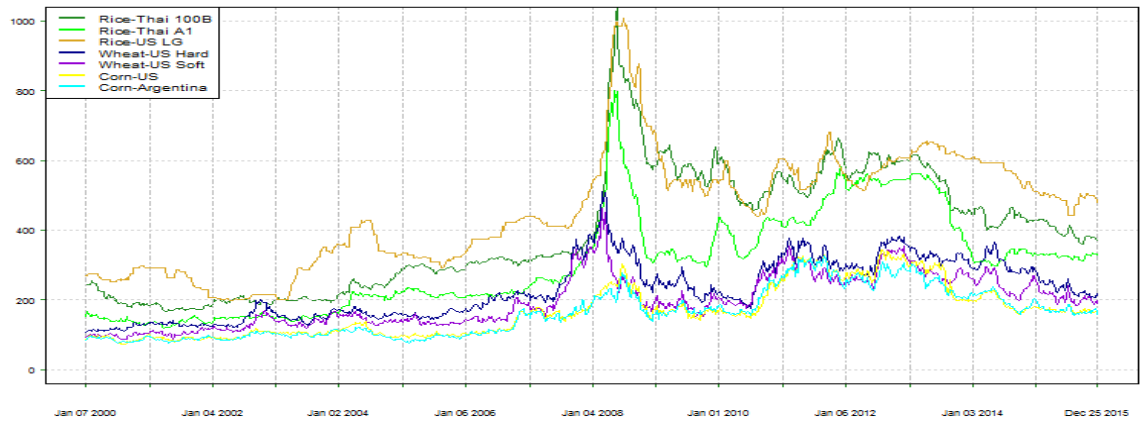

Figure 4. Food grain prices (USD/ton).

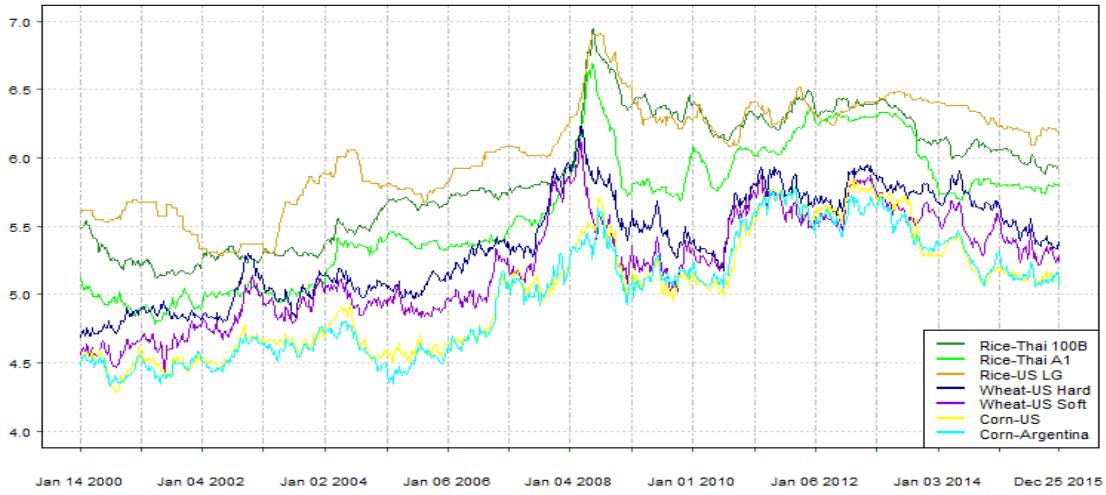

Figure 5. Food grain prices (log prices)

Figure 6. Returns of food grain prices (change in log prices)

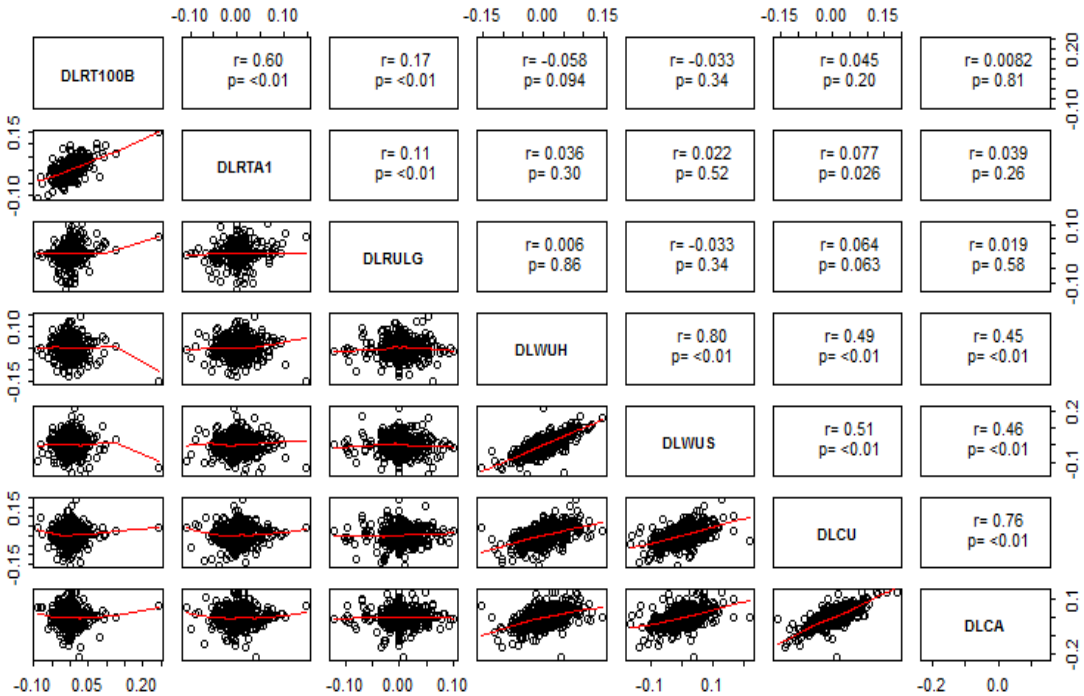

Figure 7. Scatterplot matrix and correlation among log price changes

2.4. Results and Discussion

In this section, results from the GARCH(1,1) model and the copulas are presented. First, the results from GARCH(1,1) for the marginal models are analyzed; then the copula results are presented and analyzed.

2.4.1. Marginal: GARCH Process

The parameter estimates and the standard errors of the univariate GARCH models for marginal distribution are presented in Table 11. The skewness coefficients, which capture asymmetry in the distribution, are significant for each series, which justifies the rationale of using the skewed student *t* GARCH process. Each skewness coefficient in the GARCH models is positive, suggesting that the tail of the marginal distribution is longer on the right side. This

implies that large positive price changes, often observed during price booms, are more likely than large negative price changes of the same magnitude. The results corroborate the descriptive statistics presented in Table 9. The shape parameter estimates depict the fact that wheat prices have fattest tails, with coefficients of 10.0, followed by the corn markets in the United States and Argentina respectively. Table 11 also presents results for several tests that check whether models for the margins are well specified. Table 11 presents the test statistics and the *p*-values of those tests. The Jerque-Bera (JB) test and Shapir-Wilk (SW) test confirm that marginal models are well specified for each price series. Table 11 also presents the *p*-values for the Ljung-Box test of autocorrelation in the squared residuals of the skewed student *t* GARCH fits and the *p*-values for the ARCH LM test. All these results imply that the marginal model for each series is well specified. The residuals from the GARCH fits are extracted and are transformed into cumulative distribution functions of uniform distribution with a range between 0 and 1. These transformed uniform distributions are used for modeling the dependence structure among commodity markets using copulas.

Table 11: GARCH(1,1) Results

Variables	α	β	**skew**	**shape**	**JB Test**	**SW Test**	**Ljung-Box Test**			**LM ARCH**
							10	15	20	
Rice (100%B, Thai)	0.43***	0.47***	1.02***	3.92***	306	0.96	56.9	62.1	63.2	15.4
	(0.15)	(0.17)	(0.05)	(0.65)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.22)
Rice (A1Super, Thai)	0.29***	0.84***	1.07***	2.49***	329	0.94	68.7	69.4	71.9	15.54
	(0.14)	(0.03)	(0.04)	(0.29)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.21)
Rice (Long Grain, USA)	1.00***	0.31	1.00***	2.12***	6356	0.05	0.10	0.12	0.12	0.051
	(0.11)	(0.03)	(0.01)	(0.01)	(0.00)	(0.00)	(0.99)	(0.99)	(0.99)	(0.99)
Wheat (Hard, USA)	0.13***	0.83***	1.08***	10.0***	18.7	0.99	3.5	8.2	9.89	12.4
	(0.04)	(0.05)	(0.06)	(2.95)	(0.00)	(0.01)	(0.96)	(0.91)	(0.97)	(0.41)
Wheat (Soft, USA)	0.15***	0.78***	1.02***	10.0***	15.5	0.99	6.2	11.99	13.6	12.25
	(0.04)	(0.06)	(0.05)	(2.56)	(0.00)	(0.03)	(0.80)	(0.68)	(0.85)	(0.42)
Corn (USA)	0.13***	0.79***	1.07***	7.21***	43.46	0.99	4.94	13.3	16.9	14.98
	(0.04)	(0.06)	(0.05)	(1.80)	(0.00)	(0.00)	(0.89)	(0.58)	(0.66)	(0.24)
Corn (Argentina)	0.003**	0.96***	1.07***	5.6***	118.9	0.98	3.67	7.75	15.5	17.57
	(0.01)	(0.01)	(0.05)	(1.12)	(0.00)	(0.00)	(0.96)	(0.93)	(0.75)	(0.13)

Note. For model parameters, standard errors are presented in parentheses. For test statistics, *p*-values are presented in parentheses.

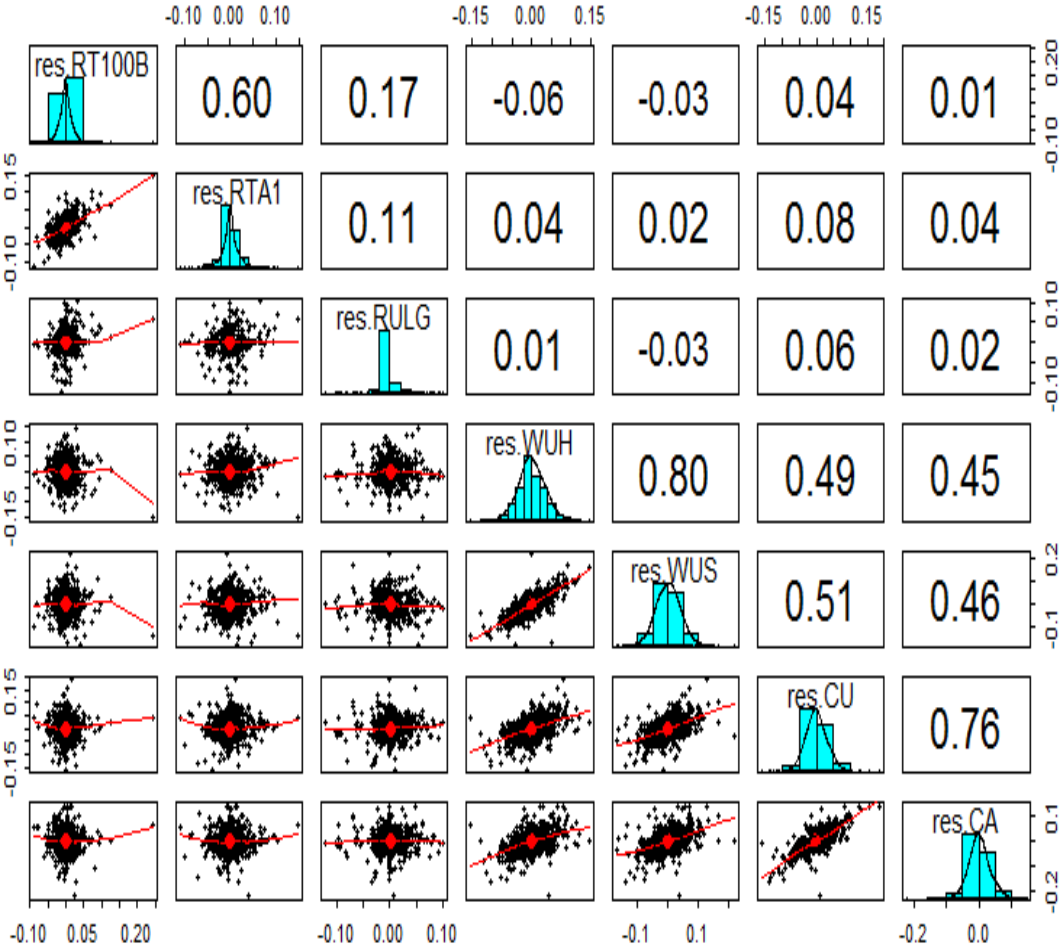

Figure 8. Scatterplot matrix and correlations among standardized residuals.

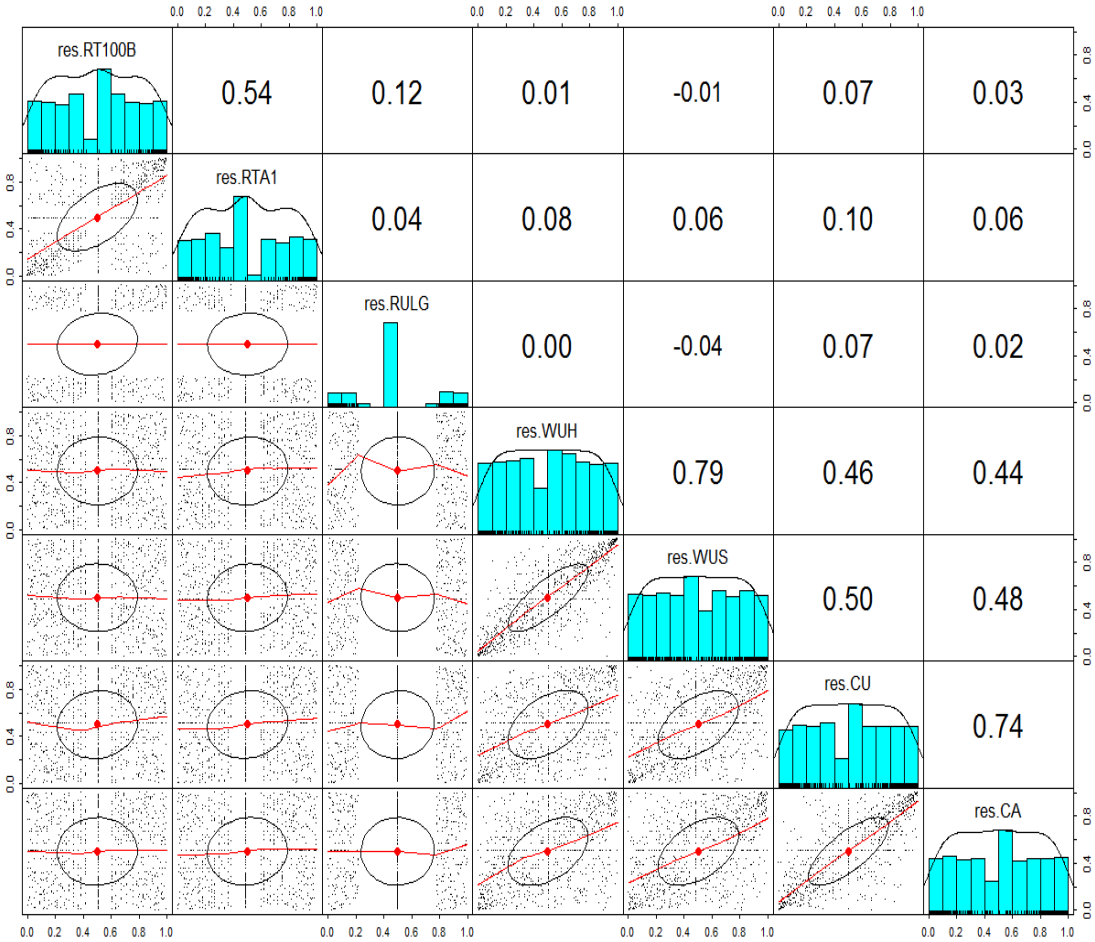

Figure 9. Scatterplots and correlations when residuals were transformed into uniform CDF.

2.4.2. Copula Results

Three approaches have been used to estimate the dependence structure in global food grain markets using copulas. First, the dependence structure between pairs of price returns has been estimated using a Gaussian copula; this gives a glimpse of the dependence structure that is captured by models in existing literature. Estimates of parameters and Kendall's tau using a Gaussian copula are presented in Table 12. Second, a copula family from a wide variety of copulas that capture asymmetric dependence structures and tail dependence is chosen using

the AIC to model pairs of price series. Estimated parameters and Kendall's tau values from the selected copula family are presented in Table 13. Finally, the multivariate vine copula models are implemented. Both the C-vine and D-vine copula models are estimated, and the results are shown in Tables 14 and 15, respectively. Upon estimation of both specifications, Vuong's (1989) non-nested specification test was performed. This test's statistics and other goodness-of-fit statistics (Akaike information criterion (AIC) and Bayesian information criterion (BIC)) are presented in Table 15. The test statistics weakly favor the D-vine specification; the D-vine model has a higher log-likelihood value and smaller AIC and BIC values. The ordering of data is important in Vine copula estimation as the estimates are not invariant with respect to ordering. The possible orderings increase exponentially with the number of variables under consideration. Like Goodwin & Hungerford (2014), we have followed the heuristic approaches to determining the ordering of data (which is applied to both the C-vine and D-vine models) and the resulted ordering of variables for the D-vine model is R1, R2, R3, W2, W1, C1, C2. The resulting vine copula parameter estimates along with the pair-wise copulas are presented in Table 14 and 15.

2.4.2.1. Gaussian Copula

In the case of the wheat and corn markets, the parameter estimates from the Gaussian copula model are statristically significant (Table 12). The Gaussian copula parameter estimates for the pairs of rice prices are statistically significant. The parameters for the pairs between the rice prices and the wheat prices and for the pairs between the rice prices and the corn prices are statistically insignificant, which corroborates the correlation results that were presented in the earlier section. Values of Kendall's tau for most pairs are tiny, especially for the pairs of

price returns between the rice market and the wheat or corn markets. The low Kendall's tau values between rice prices and other food grain prices indicate a minimal level of dependence between the rice markets and the other food grain markets. However, the question remains: If the dependence among the global food grain markets is so low, how did a demand shock in the U.S. corn market cause Asian rice prices to surge so sharply in the late 2000s? The use of copula models that capture asymmetric tail dependence, which the Gaussian copula fails to do, may shed light on this explanation.

Table 12: Parameter Estimates and Kendall's Tau of Gaussian Copula

Market Pairs	Parameters	Standard. Errors	Log Likelihood	Cramér von Mises statistic	Kendall's Tau
R1R2	0.570***	0.020	159.8	2.82***	0.39
R1R3	0.154***	0.036	8.69	8.74***	0.10
R1W1	-0.007	0.035	0.017	1.16**	0.00
R1W2	-0.009	0.035	0.03	1.50***	-0.01
R1C1	0.052	0.035	1.096	1.56***	0.03
R1C2	0.012	0.035	0.057	1.42***	0.01
R2R3	0.075**	0.037	2.033	8.46***	0.05
R2W1	0.067**	0.035	1.811	1.60***	0.04
R2W2	0.049	0.035	0.98	1.43***	0.03
R2C1	0.093***	0.035	3.48	1.49***	0.06
R2C2	0.058*	0.035	1.35	1.40***	0.04
R3W1	-0.006	0.037	0.013	8.35***	0.00
R3W2	-0.042	0.037	0.648	7.99***	-0.03
R3C1	0.068*	0.037	1.67	8.46***	0.04
R3C2	0.017	0.037	0.101	8.21***	0.01
W1W2	0.810***	0.009	440.5	0.89	0.60
W1C1	0.496***	0.024	115.5	0.84	0.33
W1C2	0.470***	0.025	101.9	1.36***	0.31
W2C1	0.518***	0.023	127.7	1.26**	0.35
W2C2	0.487***	0.024	110.2	0.80	0.32
C1C2	0.766***	0.011	363.9	1.45***	0.56

Note. * indicates the significance of the coefficients at 10% or lower level.

2.4.2.2. Non-Gaussian Copula

Parameter estimates from the selected copula family, which is selected based on AIC, are presented in Table 13. Here, only copula families that can capture the tail dependence between the price pairs are considered. The study excludes the student *t* copula because it cannot be estimated when the degrees-of-freedom parameter is less than 2; few market pairs truly ended up with degrees-of-freedom parameters lower than 2, but this should not weaken the results, because the Gaussian copula has been estimated separately for comparison with the selected copula family. Table 13 shows that parameter estimates and Kendall's tau values improve slightly when a copula family that captures tail dependence is used. The dependence between the Asian rice market and other food grain markets in the United States and Argentina is low. The level of dependence between the corn markets and the wheat markets, however, is found to be strong. Particularly, the upper tail dependence among corn markets and wheat markets are found to be strong, implying a very high level of dependence during "up days."

Two plausible reasons can be argued for this dependence structure among global food grain markets. First, the elasticity of substitution between rice and other food grains is low due to food habits and consumer tastes. Second, there is a great geographical distance between the center of the rice market in Asia and the centers of the corn and wheat market in the United States. Even though the parameters are statistically significant, there is a very low level of dependence between the Asian rice prices and the U.S. rice prices. A modest upper tail dependence between the R2 in Thailand and the R3 in the United States has been found using an estimation of the Joe copula model. Some tail dependencies are quite high for pairs of markets of corn and wheat; according to these results, the empirical evidence does not support

the argument that shock transmission occurred between the U.S. corn market and the Asian rice markets in the late 2000s. The results also imply that speculation is not a plausible explanation for the rice price boom in the 2000s, because speculation and arbitrage behavior in the futures market are thought to have affected Asian rice markets by affecting the U.S. grain markets. However, demand shock in the U.S. corn market and speculation and arbitrage behavior in the U.S. futures market may have indirectly influenced the Asian rice markets by creating a situation that led to panicked responses from the major food grain supplier countries: export bans and restrictions on exports.

Table 13: Parameter Estimates, Kendall's Tau, and Tail Dependence Estimates of Selected Copula Family

Market Pairs	Copula Family	Param. I	*SE* I	Param. II	*SE* II	Kendall Tau	Tail Dependence	
							L. Tail	U. Tail
R1R2	Survival Clayton-Gumbel	0.41***	0.078	1.42***	0.058	0.417	0.373	0.615
R1R3	Survival Clayton	0.18***	0.045			0.081		0.019
R1W1	Survival Clayton	0.008	0.037			0.004		
R1W2	Rotated Joe (270)	-1.06**	0.027			-0.031		
R1C1	Joe-Frank	1.419	0.500	0.632**	0.360	0.054		
R1C2	Survival Clayton	0.023	0.037			0.012		
R2R3	Joe	1.07***	0.028			0.036		0.082
R2W1	Survival Gumbel	1.044**	0.022			0.042	0.057	
R2W2	Survival Gumbel	1.042**	0.021			0.040	0.055	
R2C1	Survival Gumbel	1.058**	0.023			0.055	0.075	
R2C2	Survival Gumbel	1.037**	0.022			0.035	0.049	
R3W1	Survival Joe	1.019	0.023			0.011	0.026	
R3W2	Survival Joe	1.010	0.021			0.006	0.014	
R3C1	Survival Gumbel	1.055**	0.023			0.052	0.071	
R3C2	Joe	1.031	0.029			0.017	0.000	0.041
W1W2	Clayton-Gumbel	0.49***	0.084	2.084***	0.091	0.614	0.506	0.605
W1C1	Survival Clayton-Gumbel	0.31***	0.070	1.273***	0.047	0.320	0.276	0.580
W1C2	Survival Clayton-Gumbel	0.21***	0.067	1.320***	0.048	0.314	0.310	0.592
W2C1	Survival Clayton-Gumbel	0.34***	0.073	1.301***	0.049	0.342	0.296	0.587
W2C2	Survival Clayton-Gumbel	0.29***	0.072	1.298***	0.049	0.326	0.294	0.586
C1C2	Survival Clayton-Gumbel	0.61***	0.092	1.786***	0.079	0.571	0.526	0.678

Note. * indicates the significance of the coefficients at 10% or lower level.

2.4.2. 3. Multivariate Copulas: The C-Vine and the D-Vine

Although the D-vine copula is slightly favored by the criterion of log likelihood, the AIC and BIC, the Vuong test, and the Clarke test do not significantly favor the D-vine copula over the C-vine copula. Therefore, the results from both the C-vine copula and the D-vine copula are presented in Table 14 and 15, respectively.[15] The copula family for each pair, which is selected from the set of copulas that are capable of modeling asymmetric dependence, is selected based on which copula family has the lowest AIC. The log-likelihood values are larger in the vine copula model (Table 14 and 15) than that of the Gaussian copula (Table 13), implying a superior fit of the vine models. Most parameters are found statistically significant in both models, implying statistically significant dependence among the food grain markets. However, the dependence measure, the Kendall's tau, and the Tree plots (B1 and B2 in Appendix B) show high dependence only between the wheat market and the corn market, not with the rice market. The results indicate weak dependence between the pairs of prices from the rice market and the other food grain markets. Therefore, the results from the multivariate copulas also confirm that global food grain markets are clustered according to geographical proximity.[16] Therefore, the results do not support either of the following hypotheses: that the price surge in the Asian rice markets in the late 2000s was mainly driven by the demand shock in the U.S. corn markets caused by changes in the U.S. ethanol policy in 2007 or that the price surge was caused by speculation and arbitrage behaviors in the futures market. The results indicate that the late 2000s commodity price boom in food grain supplier countries skyrocketed

[15] The standard errors for the C-Vine and the D-vine copula parameters have been generated through the transformation of D-vine to regular vine (R-vine) copula.

[16] Further research on costs and time of intercontinental food grain transportation could shed light on these results, which indicate that food grain markets around the world are clustered by geographical proximity.

rice prices in the Asian markets because of panicked responses such as the rice export bans of India and Vietnam (Carter et al., 2011).

Table 14: *C*-Vine Copula Model Parameter Estimates

Factorization	**Copula Family**	**Param. 1**	***SE* I**	**Param. II**	***SE* II**	**Kendall Tau**
R1R2	Survival Clayton-Gumbel	0.408***	0.078	1.424***	0.058	0.417
R1R3	Survival Clayton	0.176***	0.045		0.000	0.081
R1W1	Survival Clayton	0.008	0.037		0.000	0.004
R1W2	Rotated Joe (270)	-1.056**	0.027		0.000	-0.031
R1C1	Joe-Frank	1.419***	0.500	0.632**	0.360	0.054
R1C2	Survival Clayton	0.023	0.037		0.000	0.012
R2R3|R1	Rotated Clayton (90)	-0.043	0.038		0.000	-0.021
R2W1|R1	Joe-Frank	3.135	12.472	0.223	1.084	0.063
R2W2|R1	Survival Gumbel	1.030	0.021			0.029
R2C1|R1	Clayton	0.103***	0.039			0.049
R2C2|R1	Survival Joe	1.058***	0.028			0.032
R3W1| R1R2	Rotated Clayton (90)	-0.041	0.038			-0.020
R3W2| R1R2	Rotated Gumbel (90)	-1.029	0.021			-0.028
R3C1| R1R2	Survival Joe	1.073**	0.032			0.040
R3C2|R1R2	Rotated Joe (90)	-1.029	0.026			-0.016
W1W2| R1R2R3	Clayton-Gumbel	0.396***	0.080	2.123***	0.092	0.607
W1C1| R1R2R3	Survival Clayton-Gumbel	0.310***	0.069	1.264***	0.046	0.315
W1C2|R1R2R3	Survival Clayton-Gumbel	0.219***	0.067	1.310***	0.047	0.312
W2C1| R1R2R3W1	Survival Joe-Frank	6.000	8.581	0.259	0.361	0.171
W2C2| R1R2R3W1	Joe-Frank	6.000	11.042	0.249	0.454	0.164
C1 C2|R1R2R3W1W2	Clayton-Gumbel	0.332***	0.077	1.651***	0.069	0.481

Note. * indicates the significance of the coefficients at 10% or lower level.

Table 15: D-Vine Copula Model Parameter Estimates

Factorization	**Copula family**	**Param. 1**	***SE* I**	**Param. II**	***SE* II**	**Kendall's tau**
R1R2	Clayton-Gumbel	0.408***	0.078	1.424***	0.058	0.417
R2R3	Joe	1.065**	0.028			0.036
R3W1	Survival Joe	1.019	0.023			0.011
W1W2	Clayton-Gumbel	0.488***	0.084	2.084	0.091	0.614
W2C1	Survival Clayton-Gumbel	0.338***	0.073	1.301***	0.049	0.342
C1C2	Survival Clayton-Gumbel	0.613***	0.092	1.786***	0.079	0.571
R1R31|R2	Joe-Frank	6.000	13.907	0.150	0.369	0.092
R2W1|R3	Survival Clayton	0.094**	0.042			0.045
R3W2|W1	Rotated Clayton (270)	-0.047	0.039			-0.023
W1C1|W2	Gumbel	1.072***	0.022			0.067
W2C2|C1	Gumbel	1.094***	0.024			0.086
R1W1|R2 R3	Rotated Clayton (90)	-0.042	0.036			-0.021
R2W2|R3W1	Joe	1.035	0.027			0.020
R3C1|W1W2	Gumbel	1.059**	0.024			0.055
W1C2| W2 C1	Survival Gumbel	1.031*	0.019			0.031
R1 W2|R2 R3W1	Survival Clayton	0.025	0.030			0.013
R2 C1| R3W1 W2	Gumbel	1.032*	0.021			0.031
R3C2|W1W2C1	Rotated Clayton (90)	-0.034	0.035			-0.017
R1C1|R2R3W1W2	Joe-Frank	1.287***	0.434	0.661	0.438	0.041
R2C2|R3W1W2C1	Rotated Clayton (90)	-0.031	0.034			-0.015
R1 C2|R2R3W1W2C1	Rotated Joe (270)	-1.029	0.022			-0.016
C-vine AIC		-2412.68				
D-vine AIC		-2454.4				
C-vine BIC		-2270.93				
D-vine BIC		-2326.8				
C-vine log-likelihood		1236.34				
D-cine log-likelihood		1254.2				
Vuong test (C-cine vs. D-vine)		-1.6				
Vuong test *p*-value		0.11				
Clarke test (C-vine vs. D-vine)		397				
Clarke test *p*-value		0.19				

Note. * indicates the significance of the coefficients at 10% or lower level.

2.4.3. Robustness Checks

The results from three different set of copulas, which are similar in nature, seem robust; all imply that global food grain markets are clustered according to geographical proximity. However, the robustness of the results has been examined further to ensure that policy conclusions derived from the results are dependable.

Three approaches are used to check the robustness of the results reported in the preceding subsection. First, the study examines the dependence structure between the rice markets and the other markets by using current week's price changes in the rice market along with the previous week's price change in the wheat/corn markets. It is often argued that shock transmission in food grain markets takes some time, and that the current period's rice price changes may reflect last week's wheat/corn price changes. If this argument is true, we expect a higher level of dependence between the rice market and the wheat/corn markets under the new setting than the previous setting that estimated the dependence structure between rice market and the wheat/corn markets using the current week's price changes for all crops. (The study has also tested the reverse pattern.) Second, the study tests the robustness of the results by comparing the level of concordance between the extreme price changes for different crops. This exercise shows that the degree of extreme price changes in one market is echoed in another market. Third, the study simulates the uniform marginal distributions using the estimated copula parameters and compares them with the original data.

The results for the various copula families used to compare current rice price changes with lagged wheat/corn price changes are presented in Table 16 and Figure 10. Both the copula results presented in Table 16 and the scatter plot in Figure 10 show no significant deviations from our original results. The level of upper tail dependence between the U.S. long grain rice market, Thailand's 100% Broken rice market, and Thailand's A1 Super rice market increased to 0.13 from 0.02 and to 0.12 from 0.08, respectively. However, the overall dependence between the rice markets and the wheat/corn markets, measured by the Kendall's tau, remains low.

When the current prices for the U.S. food grain markets and Argentina's corn market are modeled with the lagged rice prices in Thailand, the upper tail dependence between the U.S. rice market and the Thai rice markets increases even more, implying that the U.S. rice markets were responding to shocks in Thai rice market. This dynamic is plausible, given the fact that the U.S. rice market is not a large share of the global rice market, and it thus has little power to affect global rice markets.

Table 16: Parameter Estimates, Kendall's Tau and Tail Dependence Estimates of Selected Copula Family

Market pairs	Copula family	Param. I	*SE* I	Param. II	*SE* II	Kendall tau	Tail dependence	
							L. Tail	U. Tail
R1R2	Survival Clayton-Gumbel	0.423***	0.079	1.42***	0.058	0.418	0.371	0.614
R1R3	Joe	1.104***	0.033			0.056		0.126
R1W1	Clayton	0.048	0.039			0.023	0.000	
R1W2	Rotated Joe	1.040	0.029			0.023	0.053	
R1C1	Clayton	0.071*	0.040			0.034	0.000	
R1C2	Survival Joe	1.068**	0.032			0.038	0.087	
R2R3	Joe	1.096***	0.032			0.052		0.117
R2W1	Gumbel	1.013	0.019			0.013		0.018
R2W2	Survival Gumbel	1.026	0.020			0.025	0.035	
R2C1	Survival Gumbel	1.034*	0.021			0.033	0.045	
R2C2	Survival Joe	1.009	0.020			0.005	0.013	
R3W1	Survival Joe	1.019	0.023			0.011	0.025	
R3W2	Survival Joe	1.010	0.021			0.005	0.013	
R3C1	Survival Gumbel	1.053**	0.023			0.051	0.069	
R3C2	Joe	1.030	0.029			0.017		0.040
W1W2	Clayton-Gumbel	0.488***	0.084	2.08***	0.091	0.614	0.506	0.605
W1C1	Survival Clayton-Gumbel	0.309***	0.070	1.27***	0.047	0.319	0.275	0.580
W1C2	Survival Clayton-Gumbel	0.207***	0.067	1.32***	0.048	0.314	0.309	0.592
W2C1	Survival Clayton-Gumbel	0.339***	0.073	1.3***	0.049	0.342	0.295	0.586
W2C2	Survival Clayton-Gumbel	0.287***	0.072	1.3***	0.049	0.326	0.293	0.586
C1C2	Survival Clayton-Gumbel	0.614***	0.092	1.78***	0.079	0.571	0.525	0.678

Note. * indicates the significance of the coefficients at 10% or lower level.

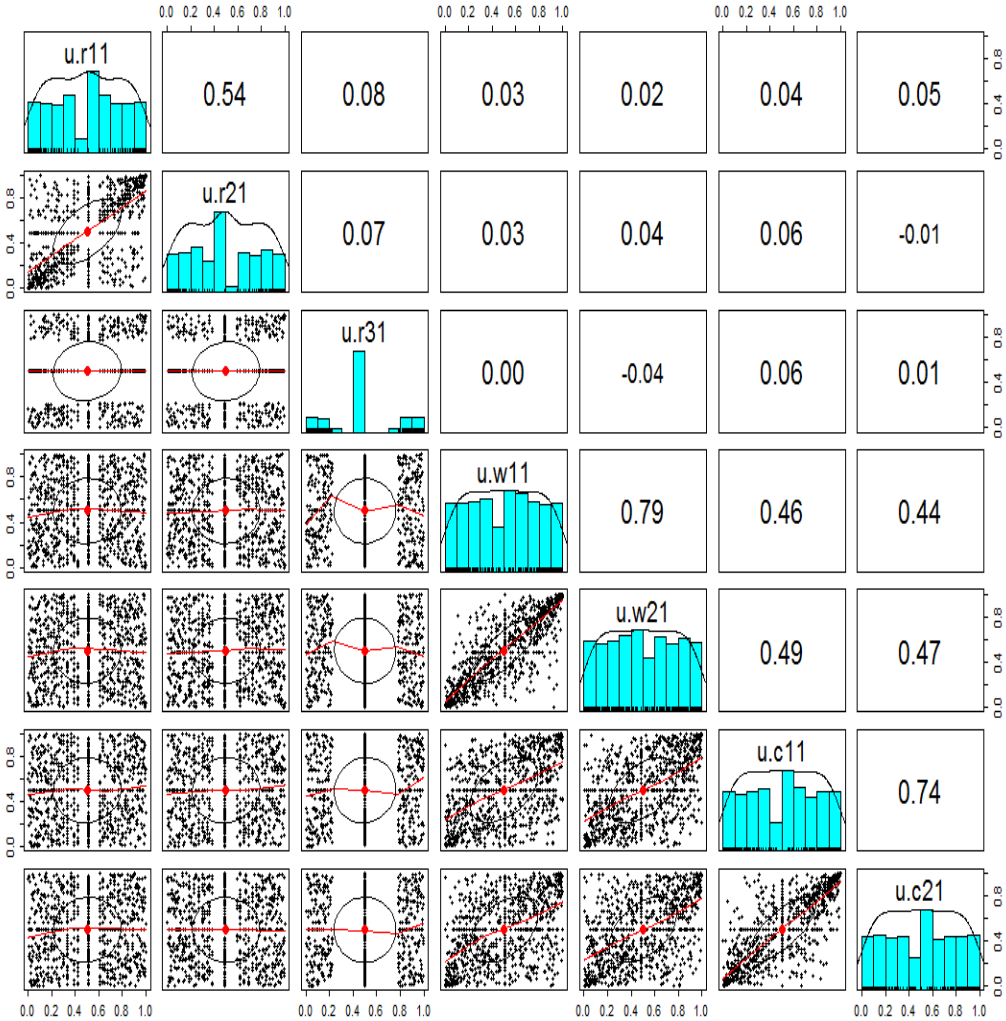

Figure 10. Scatter and tau for current rice price and lagged price changes for other crops.

Table 17 : Parameter Estimates, Kendall's Tau and Tail Dependence Estimates of Selected Copula Family

Market pairs	Copula family	Param. I	*SE* I	Param. II	*SE* II	Kendall tau	Tail dependence	
							L. tail	U. tail
R1R2	Survival BB1	0.406***	0.078	1.426***	0.058	0.417	0.374	0.615
R1R3	Gumbel	1.122***	0.027			0.109		0.145
R1W1	Rotated Joe (270)	-1.082***	0.031			-0.045		
R1W2	Rotated Joe (270)	-1.083***	0.032			-0.045		
R1C1	Survival Joe	1.022	0.025			0.013	0.030	
R1C2	Survival Clayton (270)	-0.080**	0.039			-0.038		
R2R3	Survival Clayton	0.193***	0.046			0.088		0.027
R2W1	Survival Gumbel	1.023	0.019			0.022	0.031	
R2W2	Survival Joe (270)	-1.044*	0.027			-0.025		
R2C1	Survival Joe	1.058**	0.027			0.032	0.075	
R2C2	Survival Joe	1.029	0.024			0.017	0.039	
R3W1	Survival Joe	1.019	0.023			0.011	0.026	
R3W2	Survival Joe	1.010	0.021			0.006	0.014	
R3C1	Survival Gumbel	1.055***	0.023			0.052	0.071	
R3C2	Joe	1.031	0.029			0.017		0.041
W1W2	Clayton-Gumbel	0.487***	0.084	2.084***	0.091	0.614	0.506	0.605
W1C1	Survival Clayton-Gumbel	0.310***	0.070	1.273***	0.047	0.320	0.276	0.580
W1C2	Survival Clayton-Gumbel	0.208***	0.067	1.320***	0.048	0.314	0.309	0.591
W2C1	Survival Clayton-Gumbel	0.339***	0.073	1.300***	0.050	0.343	0.296	0.587
W2C2	Survival Clayton-Gumbel	0.287***	0.072	1.297***	0.049	0.326	0.293	0.586
C1C2	Survival Clayton-Gumbel	0.615***	0.092	1.786***	0.079	0.572	0.526	0.678

Note. * indicates the significance of the coefficients at 10% or lower level.

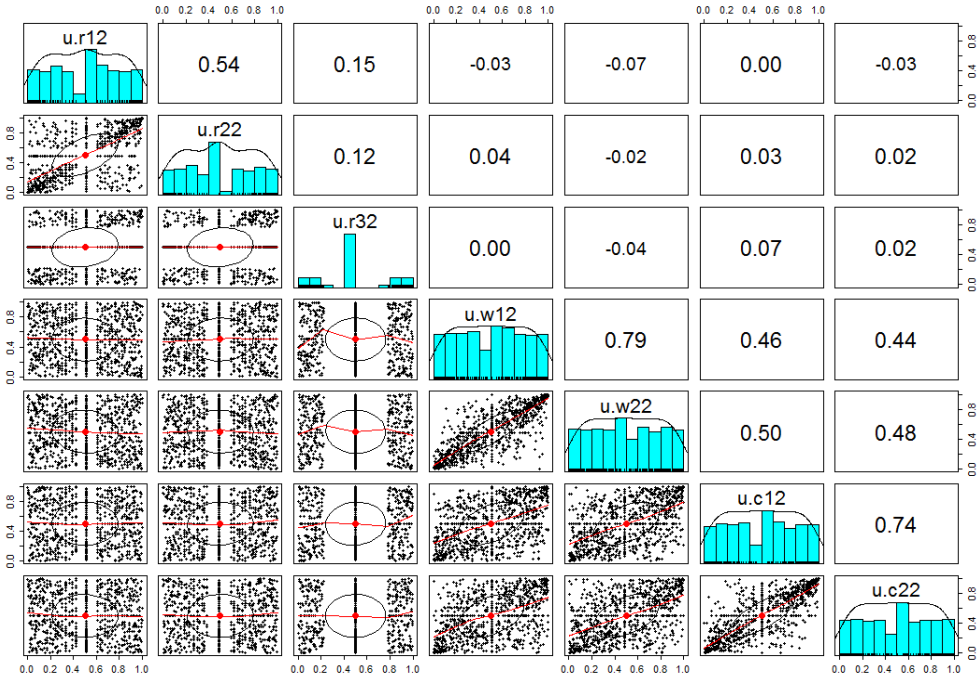

Figure 11. Scatter and tau for lagged rice price and current price changes for other crops.

The second approach to testing the robustness of our results is to examine the degree of concordance between the extreme price changes for food grains. For example, we have identified the top 10% price changes for each food grain and compared what percentage of this top 10% price changes match with the top 10% of other crops. Even the extreme 10% price changes of a food grain are matched with the 75th to 90th percentile of price changes in other crops. A weak level of concordance in price changes is evident across the crops; a strong level of concordance is obvious in two price changes within the same crop. For example, in only 6% of those weeks where Thai 100% Broken rice experiences price changes above the 90th percentile does the U.S. corn market show similar price changes (above the 90th percentile). Even the level of concordance between the extreme price changes of the Thai rice market and the extreme price changes of the U.S. rice market is quite low. Only one-fifth of the weeks that

experience price changes above the 90th percentile in the Thai market are matched with the price variations in the top 10% in the US rice market. This pattern of concordance remains similar for extreme price changes downward as well. This illustrative example thus also confirms that there is a very low level of dependence between the Asian rice market and the other food grain markets.

Table 18: Comovements of Extreme Price Changes

		RT100B	RTA1	RTULG	WUHR	WUSR	CUR
				Top 10%			
RT100B	Top 10%		45.35	19.51	9.78	11.24	6.25
	Pctile75–90		22.09	7.32	10.87	13.48	20
RTA1	Top 10%	46.99		15.85	14.13	13.48	10
	Pctile75–90	21.69		14.63	10.87	12.36	16.25
RTULG	Top 10%	19.28	15.12		9.78	7.87	13.75
	Pctile75–90	14.46	10.47		19.57	12.36	13.75
WUHR	Top 10%	10.84	15.12	10.98		64.04	40
	Pctile75–90	15.66	18.6	23.17		20.22	26.25
WUSR	Top 10%	13.51	15.38	9.09	61.96		42.25
	Pctile75–90	9.46	12.82	11.69	21.74		15.49
CUR	Top 10%	6.02	9.3	13.41	34.78	33.71	
	Pctile75–90	20.48	16.28	23.17	21.74	29.21	
CAR	Top 10%	6.02	10.47	14.63	33.7	34.83	61.25
	Pctile75–90	13.25	12.79	17.07	19.57	25.84	27.5
				Bottom 10 %			
RT100B	Pctile10–25		31.76	13.79	12.2	14.46	17.5
	Bottom 10%		41.18	18.39	7.32	7.23	7.5
RTA1	Pctile10–25	18.07		10.34	19.51	19.28	30
	Bottom 10%	42.17		20.69	9.76	10.84	11.25
RTULG	Pctile10–25	13.25	12.94		8.54	6.02	8.75
	Bottom 10%	19.28	21.18		12.2	13.25	16.25
WUHR	Pctile10–25	16.87	17.65	18.39		24.1	17.5
	Bottom 10%	7.23	9.41	11.49		61.45	40
WUSR	Pctile10–25	8.11	12.82	18.75	30.49		21.52
	Bottom 10%	8.11	11.54	13.75	62.2		41.77
CUR	Pctile10–25	8.43	15.29	20.69	21.95	19.28	
	Bottom 10%	7.23	10.59	14.94	39.02	39.76	
CAR	Pctile10–25	10.84	12.94	12.64	25.61	13.25	28.75
	Bottom 10%	12.05	11.76	13.79	45.12	39.76	53.75

Finally, uniform marginal distributions have been simulated using the estimated copula parameters to illustrate how well the copulas fit with the real data. The simulated data for pairs of price changes using the bivariate Gaussian copula parameter and the bivariate non-Gaussian copula parameter are presented alongside the actual data in scatterplots in Figure B3 in Appendix B. Simulated data using the parameter estimates of selected copula families other than Gaussian copula are, in most cases, close to the real observation. Simulated data from the C-vine and D-vine multivariate copulas are also close to the actual observation (Figure B4–B6 in Appendix B). Thus, these figures indicate that copula families that allow for asymmetric dependence and capture tail dependence provide better estimates of dependence structure among the food grain markets. All three robustness check approaches presented here led us to conclude that the estimates of dependence measures in this chapter are reliable and robust, and thus that the dependence between the food grain markets around the globe is clustered based on geographical proximity.

2.5. Concluding Remarks

This chapter explores the dependence structure among the global food grain markets using a novel approach: copulas. While traditional time-series models under the assumption of a Gaussian distribution tend to conclude that there is a high level of dependence and volatility transmission among global food grain markets, the use of non-Gaussian copulas that capture asymmetric dependence led to the conclusion that global food grain markets are clustered: they are more dependent on geographically near markets than on distant ones. This finding could help policy-makers formulate policies on an informed basis, rather than responding in a panicky fashion to production or demand shock in other food grain markets. These estimates

could also serve as risk management tools in future policy formulation and price forecasting, serving both speculators in the commodity futures markets and policy-makers tasked with ensuring food security.

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CHAPTER 3: THE EFFECT OF EXCHANGE RATE UNCERTAINTY ON TRADE FLOWS: EVIDENCE FROM IMPLIED OPTIONS VOLATILITY

3.1. Introduction

The effect of exchange rate volatilities on trade flows drew broad interest from economists when the Bretton Woods fixed exchange rate system broke down in the 1970s. The floating exchange rate system that replaced the Bretton Woods system allows the value of currency to fluctuate based on the foreign exchange market fundamentals. Smith (1999) reviews studies examining the impact of exchange rate volatilities on trade flows and finds that the empirical evidence is mixed. Early studies (for example, Cushman, 1983; Thursby & Thursby, 1987; and Bini-Smaghi, 1991) tend to find high negative impacts of exchange rate volatility on trade volume; however, later studies (see Frankel & Wei, 1995; Sercu & Vanhulle, 2003) find no such evidence, seeing instead only small effects on trade volume from exchange rate volatility. McKenzie (1999) also surveys a large body of empirical paper on the trade effects of exchange rate volatilities and observes mixed results. The volatility of foreign exchange rates increases firms' uncertainties about expected profit (Hooper & Kohlhagen, 1978; Clark, 1973). Clark (1973) argues that when exporting firms face uncertainties over profit, they reduce exports and charge a higher price as a risk premium. When importers decrease imports due to exchange rate volatilities, demand decreases in international markets, which creates a surplus in exporting countries. As a result, both consumers and producers in countries engaged in foreign trade can be affected by exchange rate uncertainty. McKenzie (1999) stresses to tha point that the theoretical models could lead to a negative or positive trade effects of exchange rate volatilties depending on the attitude of the agent involved in foreign trade towards risk.

A number of studies examine the trade effects of exchange rate volatilities using aggregate data (see Akhtar & Hilton, 1984; Arize, 1996; Arize & Ghosh, 1998; Bahmani-Oskooee, 2002) and bilateral trade data (see Cushman, 1983; Ariccia, 1999; Hooper & Kohlhagen, 1978; McKenzie & Brooks, 1997; Thursby & Thursby, 1987). Another strand of literature examined the effects of exchange rate volatilities on agricultural commodity trade flows (see Cho, Sheldon, & McCorriston, 2002; Kandilov, 2008; and Villanueva & Sarker 2009).

While studies on exchange rate volatility tend to conclude that exchange rate volatility has a negative impact on trade flows, there is little consensus on the reliability of the measures of exchange rate volatility used in the literature (see Clark, Tamirisa, Wei, Sadikov, & Zeng, 2004). The lack of a generally accepted theory of the impact of exchange rate risk on the behavior of firms is in part responsible for the disagreement. Most studies use unconditional realized (ex-post) volatility measures—variants of the standard deviation of the difference in annual or monthly data (see, for example, Clark et al., 2004; Cho et al., 2002; Frankel & Wei, 1995; and Tenreyro, 2007). On the other hand, many studies use the conditional exchange rate variance, generated through a GARCH process, to capture exchange rate uncertainty ex-ante (see, for example, Kandilov, 2008; Pozo, 1992; Wang & Barrett, 2007). Kandilov (2008) measures bilateral exchange rate volatility for 69 countries by grouping them into developed, emerging, and developing economies and following a GARCH(1,1) process to generate a volatility series for each group of countries.

Although the literature shows little consensus about the measure of exchange rate volatility, the use of time-series models (e.g. GARCH process) to generate exchange rate

volatility measures remains a popular practice. The GARCH-generated volatility measure, however, is not free from criticism. The most common criticism against the GARCH-generated volatility measure is that it is a *backward*-looking measure, and trade is affected by *future* exchange rate uncertainties. Thus, measures of forward-looking exchange rate volatilities (e.g. foreign exchange options implied volatility) are necessary to examine what impact exchange rate uncertainties have on trade volume.

Day and Lewis (1992) used time-series models of volatility as a starting point and analyzed the additional forecast contribution provided by implied volatility using S&P 100 options. The results suggest that implied volatility contains additional information over GARCH models. Poon and Granger (2005) reviewed 93 studies that conducted tests of volatility forecasting methods on a broad range of financial asset returns. They found evidence that option implied volatility is superior to time-series based forecasts. Thus, in financial markets, the implied volatility of options has been proven to be a very dependable measure of volatility, and this new measure of volatility is superior over GARCH models. However, the practice of options trading in foreign exchange markets is a relatively recent phenomenon, and the foreign exchange options have become an important risk management tool for currency traders and businesses involved in foreign trade. Moreover, the high-frequency gross domestic product (GDP) data (e.g. monthly) is scarce, and exchange rate volatility studies therefore often use annual data to control the size of an economy. Until now, these limitations precluded the use of option implied volatility, the superior measure of exchange rate volatility.

GARCH models also lead to the use of low-frequency data in estimation. Most existing studies use annual or quarterly data to examine the impact of exchange rate volatility on trade

volume. Because foreign currency markets are volatile, exchange rates fluctuate greatly, even in a single day. Thus, the use of annual or quarterly exchange rate volatility measures may underestimate the true effect of actual exchange rate volatility. This study overcomes the limitations mentioned above by using a novel, and potentially superior, measure of exchange rate volatility and by using high-frequency data (monthly data). Instead of conventional volatility measures of exchange rates, this study uses foreign currency options implied volatility.[17]

The broad objective of this chapter is to examine the effects of exchange rate volatilities on trade volume using a new measure of exchange rate volatility. The study also compares the effect of exchange rate volatilities across sectors and different country groupings such as advanced economies and developing economies. This study contributes to the relevant literature in at least two ways. First, it introduces a new measure of exchange rate volatility that is entirely unprecedented in the relevant literature. While most studies tend to use a time-series based (e.g. GARCH-generated) realized volatility measure of exchange rates, I use an options implied volatility measure of exchange rates, which is a forward- rather than backward-looking measure. Second, the paper uses high-frequency data (e.g. daily exchange rate options volatility data and monthly bilateral trade data). Most studies in existing literature use yearly exports or trade flows and daily or monthly exchange rate data to generate an annual volatility of the exchange rate. Those studies ignore the potential averaging out of the impact of exchange

[17] A foreign exchange option is a derivative where the option holder has the right but not the obligation to exchange money denominated in one currency for a second currency at a pre-agreed exchange rate on a specific date. There are two types of options: American options and European options. American options can be exercised at any time before expiry, while European options can only be exercised at the expiry date. For the measure of foreign exchange options volatility, we use American options, because volatility in future markets is reflected in the daily transactions of options.

rate volatility on trade flows; this attempt may more accurately capture the impact of exchange rate volatility on trade flows.

The rest of the paper is organized in the following manner: the next section presents a discussion on the choice of exchange rate volatility measure. Section 3.3 describes our econometric specifications. Section 3.4 presents a discussion of the data, the summary statistics, and the construction of monthly GDP. Section 3.5 presents and discusses the results of estimation. Section 3.6 offers concluding remarks.

3.2. Measuring Exchange Rate Volatility

To test the trade effect of exchange rate volatilities, an appropriate measure of exchange rate volatility is necessary because there is no actual record of exchange rate volatility. Approaches to measuring volatilities include historical volatility, implied volatility, within-period volatility, moving standard deviation, and GARCH, etc. Early studies often defined the standard deviation of the real exchange rate or the logarithm of the real exchange rate as their measure of volatility. Although easy to calculate, volatility represented by standard deviation often cannot capture the persistence of the real exchange rate, whose distribution is fat-tailed.

In the current literature, the GARCH model and its extensions have been widely used to model exchange rate volatilities. However, in the case of financial asset returns, options implied volatility has been found to be superior to time-series models of volatility (Day and Lewis, 1992; Poon and Granger, 2005). Moreover, options implied volatility is a forward-looking measure of exchange rate uncertainty. Therefore, the use of foreign exchange options implied volatility can more accurately evaluate the impact of exchange rate volatilities on trade

flows. Options volatility is defined as the standard deviation of daily percentage changes in the underlying exchange rates. Like all futures markets, options volatility reacts instantaneously and negatively to unsettling economic and political events. Most currency options traders focus their activities on predicting movements of currency volatility in the short run, for they will move price the most. Furthermore, if market participants are presumed to be rational, then the market's expectation is likely to be a good predictor of future price developments. Implied volatility is usually considered to be a simple estimate of the dispersion of the market's subjective expectations' probability distribution of the future exchange rate. The subjective expectations regarding future exchange rates are reflected in the prices of currency options. Given that options are traded on the futures market and their market prices are observable, the implied volatility can be estimated using the observed options price.

In the Black-Scholes framework of options pricing formula, a theoretical value of an option on an exchange rate depends on various inputs. The inputs, that determine the value of an option, include the future realized price volatility, σ, which is an unobservable input. The Garman-Kohlhagen option model, a variation of the Black-Scholes (B-S) model, is commonly used currency options pricing model. Given the observable inputs, the price of a currency option, O_t, can be represented as $O_t = f(\sigma)$, where σ is implied-option volatility. Given the options prices are observable, f is monotonically increasing σ, and f is invertible; implied options volatility can be obtained using the function $\sigma = f^1\ (O_t)$. This volatility estimate is the subjective expectations regarding future exchange rate over the remaining life of the option.

This paper uses implied options volatility data from DataStream. The DataStream reports both the implied call and the implied put volatility and this paper uses trading-weighted

averages of the Black-Scholes based implied volatilities of all near term call or put currency options, traded over the last five days[18].

3.3. Econometric Specifications

3.3.1. Panel Fixed-Effects Model

This study uses the panel fixed-effects model to estimate the impact of exchange rate volatilities on trade flows. The following empirical model is used to assess the effects of exchange rate volatilities on the United States' trade with its major trading partners:

$$\ln TRADE_{ijt} = \beta_0 + \beta_1 lnGDP_{i,t-1} + \beta_2 POP_{i,t-1} + \beta_3 lnGDP_{j,t-1} + \beta_4 lnPOP_{j,t-1} + \beta_5 lnVOL_{ijt} + \beta_6 lnVOL^2{}_{ijt} + \beta_6 FTA_{ijt} + \mu_{ij} + \tau_t + \varepsilon_{ijt} \quad (3.1)$$

$\ln TRADE_{ijt}$ implies the log of trade volume between country i and country j at time t. As only countries that trade with the United States are considered for this study, here j stands for the United States only. $lnVOL_{ijt}$ implies the log of options volatility of the currency of country i against the U.S. Dollar at time t. Kandilov (2008) has shown that exclusion of nonlinearity in the agricultural trade effects of exchange rate may distort findings for samples that include developing economies. Thus, following the relevant literature, we include the square of the options volatility, $lnVOL^2{}_{ijt}$, as a determinant of trade. FTA_{ijt} is a dummy variable for the free trade agreements between the United States and country i at time t. Here

[18] According to Christensen and Hansen (2002), DataStream calculates the option volatilities using the following formula : $\sigma_i = \left[\frac{\sum_d^5 \sum_{t=1}^s \sigma_{idt} N_{dt}}{\sum_d^5 \sum_{t=1}^s N_{dt}}\right]$ where s is the number of series with one month to expiration. The first summation is for the last five days that enter into the calculation and N_{dt} is the number of trades d day(s) ago in series t, and σ_{idt} denotes the implied call or put volatility d day(s) ago on series t calculated using Black-Scholes foreign exchange options pricing model from current exchange rates.

μ_{ij} accounts for country-specific heterogeneity that is constant over time, while τ_t accounts for overall time-varying heterogeneity that is constant across countries. ε_{ijt} should capture an error process that varies across countries and over time with mean zero and constant variance.

The equation (3.1) can be estimated by either the fixed-effects panel model or the random-effects panel model. The fixed-effects model assumes that the intercept term captures the individual heterogeneity, which implies that every country gets its intercept while the slope coefficients remain the same (Baltagi, 2008). On the other hand, the random-effects model assumes that the unobserved time variant individual effect in (3.1), β_i, is uncorrelated with each explanatory variable (Baltagi, 2008). In fact, the ideal random-effects assumptions include all the fixed-effects assumptions plus the additional requirement that β_i is independent of all explanatory variables in all time periods.

To choose between the fixed-effects model and the random-effects model, a Hausman specification test is performed. The Hausman specification test evaluates the size of the difference in estimates about the variances of estimates (Baltagi, 2008). The Hausman test can be specified as follows:

$$H = (\hat{\beta}^{FE} - \hat{\beta}^{RE})' \times [Var(\hat{\beta}^{FE}) - Var(\hat{\beta}^{RE})]^{-1} \times (\hat{\beta}^{FE} - \hat{\beta}^{RE})$$

where $\hat{\beta}^{FE}$ is the coefficient estimate of the fixed-effects model and $\hat{\beta}^{RE}$ is the coefficient estimate of the random-effects model.

The Hausman specification evaluates the null hypothesis that there is no systematic difference between the coefficients of the fixed-effects and the random-effects models.

Rejection of the null hypothesis leads to the conclusion that the fixed-effects model is preferred over the random-effects model (Hausman 1978).

3.3.2. Panel Unit Root Tests

Though checking for the presence of the unit root in time series has been common since the 1980s, testing for the presence of the unit root in panel data analysis is a relatively recent practice (Choi, 2001; Hadri, 2000; Harris & Tzavalis, 1999; Im, Pesaran, & Shin, 2003; Levin, Lin, & Chu, 2002; Maddala & Wu, 1999). If the variables in the panel regression model are non-stationary, the standard assumptions of asymptotic analysis will not be valid and may lead to spurious regression. The problem of non-stationarity can be treated by applying a difference operator to the series.

There are multiple testing procedures available to check for panel unit roots. However, each has some limitations. The most popular panel unit root tests are the Levin, Lin, and Chu (LLC) test; the Im, Pesaran, and Shin (IPS) test; the Harris-Tzavalis (HT) test; and the Breitung test. A major limitation of the LLC, HT, and Breitung tests is the assumption that all panels have the same value of rho. The IPS (2003) test relaxes the assumption of a common rho and instead allows each group to have its own rho. The null hypothesis is that all panels have a unit root; the alternative hypothesis is that a fraction of panels is stationary.

Another advantage of using IPS is that it does not require strongly balanced data; however, there can be no gaps in each time series. The unbalanced nature of the data set for this chapter has led us to choose the IPS test, which is based on the well-known augmented

Dickey-Fuller procedure (ADF), for our panel unit root test.[19] The IPS test has often been found superior in literature that analyzes the long-run relationships in panel data. The IPS specifies a separate ADF regression for each semistructured test, with individual effects and no time trend:

$$\Delta y_{it} = \alpha_i + \rho_i y_{i,t-1} + \sum_{j=1}^{p_i} \beta_{ij} \Delta y_{i,t-j} + \varepsilon_{it} \qquad (3.2)$$

where $i = 1,...,N$ and $t = 1,..., T$. The IPS uses distinct unit root tests for the N cross-section units. Their test is based on the ADF statistics averaged across panel units. After estimating the ADF regressions for each panel unit, the average of the *t*-statistics for p_1 from the individual ADF regressions, $t_{iT_i}(p_i)$: $\bar{t}_{NT} = \frac{1}{N}\sum_{i=1}^{N} t_{iT}(p_i \beta_i)$

In the next step, the t-bar is standardized, and the standardized t-bar statistic converges to the standard normal distribution when N and T approach to infinity. The t-bar test performs better when N and T are small (Im et al., 2003). Im et al. (2003) proposed tests with cross-sectionally demeaned series for cases in which the residuals from different regressions have a common time-specific component.

3.4. Data and Descriptive Statistics

In this study, unlike earlier studies, foreign exchange options implied volatility is used to examine the impact of exchange rate risk on trade flows.[20] Because the foreign exchange

[19] Im, Pesaran, and Shin (2003) proposed a test for the presence of unit roots in panels that combines information from the time-series dimension with that from the cross-section dimension, such that fewer time observations are required for the test to have power.

[20] We use implied volatility by weighted volume, using values from the nearest expiry month options. The series switches to the next available month on the first day of the expiry month.

options market is a relatively recent development, the sample period starts in January 1999 and ends in August 2012. The study uses volatility of currencies against the U.S. Dollar because the U.S. Dollar is the most dominant vehicle currency in international trade settlements. The Bank of International Settlements (BIS) (2010) reports that the U.S. Dollar is the most traded currency against other currencies, at approximately 85%; the comparable figure for the second most traded currency, the Euro, is 39%.[21]

The primary empirical investigation is carried out with monthly data of bilateral aggregate trade volume as well as sector-wise trade volume with the United States. This chapter uses data from 18 countries, including Eurozone. A list of sample countries is provided in Table 19. Sample countries include both advanced economies (e.g. Eurozone, Canada, Denmark, Israel, Japan, etc.) and emerging economies (e.g. Brazil, China, Thailand, etc.). The trade data are expressed in U.S. Dollars. Due to a lack of continuous export- and import-price indices for each country for the complete sample period, trade values are deflated to real trade volume by using the United States export and import price index; this is because bilateral trade is considered only when the United States is one of the partners. The dependent variable in our model is the natural logarithm of real trade flows.

Table 19: List of sample countries

Advanced Economies	**Developing Countries**
Canada, Denmark, Eurozone (Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, The Netherlands, Portugal, Spain), Israel, Japan, Korea, Norway, Singapore, Sweden.	Argentina, Brazil, Chile, China, Colombia, Malaysia, Mexico, Taiwan, Thailand

The sample used in this study is limited by the availability of the quarterly GDP series, the foreign exchange options implied volatility, and the monthly bilateral trade data. This study

[21] Since two currencies are involved in every transaction, the sum of percentage shares of individual currencies equals 200%.

uses monthly data to evaluate the implications of exchange rate volatility on trade volume.[22] Therefore, the study uses a simple average of daily implied volatilities to generate the monthly implied volatility of foreign exchange options. In general, in exchange rate volatility studies, a GDP series is used to control for the size of an economy. However, calculation of monthly GDP for most economies is not yet standard practice. Though the monthly industrial production index could be used as a proxy for the GDP, it provides a limited measure of overall economic activity. Therefore, to generate a monthly series for GDP, an alternative approach has been followed; monthly GDP series for sample countries are generated from quarterly GDP series and monthly industrial production indices by applying the proportional Denton benchmarking technique.[23] We interpolate annual population data to the monthly population data by using the cubic spline. The data for the bilateral monthly trade volume is from the Dataweb of the U.S. International Trade Commission (USITC). The quarterly GDP and the monthly industrial production indices are extracted from the International Financial Statistics (IFS) of the International Monetary Fund (IMF). The study uses the data for the foreign exchange options volatility from the Thomson Reuter's DataStream. Foreign exchange options volatility with a maturity of one month has been used, in particular.

Table 20 presents summary statistics of the data used in the estimation. Although the average level of volatility is same for the emerging economies and the advanced economies, the standard deviation of foreign exchange options volatility is almost double in developing

[22] The study also uses quarterly data to estimate the trade effects of exchange rate options volatilities, as well as to check the robustness of the results found in the estimation (which used monthly data). The results are mostly similar in nature and are presented in the Appendix.

[23] The proportional Denton benchmarking technique (see Bloem et al., 2001) uses the higher frequency movements of an associated variable (in our case, monthly industrial production as an interpolator within the quarter), while enforcing the constraint that the sum of monthly GDP flows equals the observed quarterly total.

countries than in advanced economies. These summary statistics imply that traders involved in foreign trade with developing economies face much higher exchange rate uncertainties than traders involved in foreign trade with advanced economies. Given the availability of various risk management tools (e.g. foreign exchange options, futures markets) in advanced economies, traders involved in foreign trade with advanced economies are more capable of managing risks than their counterparts involved in foreign trade with emerging economies.

Table 20: Summary Statistics

		Mean	***SD***	**Min**	**Max**	***N***
Emerging economies	Total trade (million USD)	7642	10992	279.8	54267	1620
	Agriculture trade (million USD)	331.3	467.0	17.94	2814	1620
	Chemical & machinery trade (million USD)	4041	5815	80.56	28209	1620
	Manufacturing trade (million USD)	2188	3741	65.77	19698	1620
	Options Volatility Rate	10.38	6.165	1.710	54.90	1295
	Std. Dev. (Exchange Rate)	3.02	9.37	0	91.76	1295
	GDP (billion USD)	240.62	382.98	21.314	3175.0	1575
	Population (million)	200.9	395.2	15.09	1361	1620
Advanced economies	Total trade (million USD)	10933	13871	269.5	52251	1620
	Agriculture trade (million USD)	450.9	701.6	6.623	3596	1620
	Chemical & machinery trade (million USD)	6361	7489	101.4	26780	1620
	Manufacturing trade (million USD)	2248	2910	45.12	10567	1620
	Options Volatility Rate	10.40	3.581	3.464	31.65	1417
	Std. Dev. (Exchange Rate)	1.38	5.83	0.00	86.10	1417
	GDP (billion USD)	546.71	1068.00	8683	4832.0	1599
	Population (million)	62.33	99.16	3.930	331.3	1620
Full sample	Total trade (million USD)	9288	12620	269.5	54267	3240
	Agriculture trade (million USD)	391.1	598.9	6.623	3596	3240
	Chemical & machinery trade (million USD)	5201	6803	80.56	28209	3240
	Manufacturing trade (million USD)	2218	3351	45.12	19698	3240
	Options Volatility Rate	10.39	4.984	1.710	54.90	2712
	Std. Dev. (Exchange Rate)	2.16	7.77	0.00	91.8	2712
	GDP (million USD)	394.82	819.21	8.683	4832.0	3174
	US GDP (million USD)	4432.0	738.241	3112.0	5735.0	3240
	Population (million)	131.6	296.3	3.930	1361	3240
	U.S. population (million)	297.4	11.72	276.4	316.5	3240

3.5. Results and Discussions

This section presents the time-series properties of the data, the results from the fixed-effects model, and a discussion of the results. This section also presents the results of the diagnostic tests. This study has estimated the effects of exchange rate volatilities on the United States' trade volume with its principal trading partners. Table 21 presents the results of the IPS panel unit root tests. The results clearly show that the null hypothesis of a panel unit root in levels of the series can be rejected for most series except GDP and population. However, Table 21 shows that GDP is also trend stationary. Thus, as shown by the IPS test, most of the variables are stationary, both with and without time trend specifications.

Table 21: Panel Unit Root Test: Im, Pesaran, and Shin (IPS)

Variables	Without Trend	With Trend
Log (total trade)	-5.8602*** (0.0000)	-11.0382*** (0.000)
Log (agriculture)	-13.5205*** (0.0000)	-21.8949*** (0.0000)
Log (chemical & machinery)	-3.3319*** (0.0004)	-8.3541*** (0.0000)
Log (manufacturing)	-5.2618*** (0.0000)	-6.8644*** (0.0000)
Log (volatility)	-6.1832***(0.0000)	-6.7001*** (0.0000)
Standard Deviation (Exchange Rate)	-6.29***(0.000)	-8.95***(0.000)
Log (GDP)	0.6905(0.7551)	-3.5962***(0.002)
Log (population)	0.5758(0.7176)	0.6533 (0.7432)

Note. *p*-values are in the parentheses. ***, **, and * indicate rejection of the null hypothesis that all panels contain unit roots.

The Hausman test is performed to examine the appropriateness of the fixed-effects model over the random-effects model. The Hausman test statistics for all the dependent variables—aggregate trade volume as well as sectoral trade volumes—are quite high, with *p*-values of 0.000, suggesting that the fixed-effects model is preferred to the random-effects model for all the dependent variables.

Table 22: Hausman Test: Fixed vs. Random

Dependent variables	chi2(df)	Prob>chi2
Total trade	chi2(7) = 177.9	0.0000
Agriculture	chi2(7) = 55.96	0.0000
Chemical & machinery	chi2(7) = 185.7	0.0000
Manufacturing	chi2(10) = 1233.65	0.0000

H0: Random-effects model is preferred. Ha: Fixed-effects model is preferred

Table 23 reports the coefficient estimates of the fixed-effects models for the complete sample, the advanced economies, and the emerging economies. Besides the country fixed effects, the models also included the year fixed effects and the month fixed effects. The results for the complete sample are presented in the second column of Table 23. The overall *R*-squared of 0.27 implies that the explanatory variables included in the model explain 27% of total variation in bilateral trade between the United States and any other country in the sample. For the complete sample, the log of exchange rate options implied that volatility has a significant negative effect on the log of bilateral trade volume. The elasticity of trade volume on the exchange rate options implied volatility is about -0.173 (= -0.222 + 0.049), which means that a 1% change in implied volatility could lead to a decline of 0.18% in bilateral trade. The results also confirm the presence of nonlinearity in the relationship between exchange rate volatility and trade volume. Other control variables, such as GDP of trading countries, also appear statistically significant with expected sign. A 1% increase in the GDP leads to a 0.5% increase in the total monthly trade volume. The population size of the trading countries and the dummy for the free trade agreements between the trading countries do not appear to be significant.

The trade effects of foreign exchange volatility were also explored by dividing the sample countries into two broad categories: advanced economies and developing economies. The results for these two subsamples are presented in the third and fourth columns of Table

23. The coefficient of the volatility measure is not statistically significant; it even appears with an opposite sign for advanced economies. Population and the free trade agreements (FTA) dummy also remain statistically insignificant for advanced economies. However, for the sample of advanced economies, the GDP appears statistically significant and has the expected sign. Since the traders from advanced economies have access to financial futures, they are expected to hedge the risk of exchange rate volatilities (Cho et al., 2002, Kandilov, 2008, Zhang, Reed, & Saghaian, 2010). Thus, trade between the developed countries remains relatively unaffected by exchange rate volatilities.

For the sample of emerging economies, the volatility measure appears more prominent in the estimation. The elasticity of trade volume with respect to exchange rate volatility is approximately -0.24 (-0.300 + 0.063). A percentage point increase in the volatility of foreign currency reduces trade volume by 0.24%. The income variable, measured by GDP, appears statistically significant, and the United States GDP also matters for the trade volume between the United States and emerging countries. The FTA dummy appears statistically significant with a positive sign; thus FTAs with Mexico, Chile, and Colombia help to raise the bilateral trade volume significantly. The adjusted *R*-square of 0.48 implies that the covariates in the model explain 48% of total variation in the bilateral trade volume. The results presented in Table 23 imply that the negative trade effects of foreign exchange volatilities are mainly driven by the sample of emerging economies.

Table 23: Fixed Effects Panel Regression Results (Total Trade)

	Full sample	**Advanced economies**	**Emerging economies**
Log (volatility)	-0.222*	0.057	-0.300**
	(0.108)	(0.254)	(0.120)
Square of log (volatility)	0.049**	-0.005	0.063**
	(0.022)	(0.052)	(0.027)
Lag [log (GDP)]	0.474***	0.433***	0.444***
	(0.078)	(0.109)	(0.123)
Lag [log (USGDP)]	0.993***	1.020***	1.210***
	(0.187)	(0.292)	(0.263)
Log (population)	-1.113	-0.557	-1.892
	(0.679)	(0.492)	(1.311)
Log (U.S. population)	-6.074	-12.752*	8.225
	(8.629)	(6.774)	(11.94)
FTA	0.213	0.087	0.365*
	(0.124)	(0.059)	(0.170)
Country fixed effects	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Constant	32.93	68.03*	-46.57
Table 23: Continued			
	(48.75)	(36.58)	(68.17)
R-squared (within)	0.40	0.39	0.49
R-squared (between)	0.30	0.34	0.45
R-squared (overall)	0.27	0.32	0.36
No. of observations	2670	1403	1267

Note. Standard errors are in the parentheses. Significance of estimates at 0.01, 0.05, 0.10 is marked as ***, **, and *, respectively. Year dummies and month dummies were included in each specification to capture trend effects and seasonal effects in trade, respectively. Complete results are reported in the appendix.

This paper also explores the trade effects of exchange rate volatilities at the sectoral level for agricultural trade, chemical & machinery trade, and for manufacturing trade volume. For each sector, there are three separate sets of estimations: the complete sample, the advanced economies, and the emerging economies. The results are presented in Table 24. The results show that, for the full sample, the coefficients of volatility and squared-volatility appear statistically significant for chemical & machinery and for manufacturing trade volume. In disagreement with the findings of Cho et al. (2002), the coefficients of exchange rate volatilities do not appear significant for agricultural trade—not even in the emerging

economies. The results do, however, show that volatility is statistically significant for agricultural trade in the advanced economies at the 10% level. For advanced countries, the coefficients of volatility appear statistically insignificant for the chemical & machinery trade and the manufacturing trade. However, the scenarios are reversed in the sample of emerging economies, where the results show statistically significant adverse effects from exchange rate volatility on both the manufacturing trade volume and on the chemical & machinery trade volume. These results are not surprising, as traders in developing countries have limited access to commodity and financial futures markets. Previous studies, such as Arize, Osang, & Slottje (2008); Arize, Malindretos, & Kasibhatla (2003); Bahmani-Oskooee (1996); and Kandilov (2008), find similar negative trade effects of exchange rate volatilities for the sample of developing countries.

One key finding of this study is that, generally, exchange rate volatilities do not have significant effects on the trade volume of developed economies, but do have significant adverse consequences on the trade volume of emerging economies. This finding suggests that the traders and agents in the marketing chain in advanced economies may be well protected from the risk of exchange rate volatilities with the help of a variety of market-based instruments. In the last three decades, a range of innovative financial instruments (futures, options, and other derivatives) have been developed to hedge the risk of exchange rates. Most of the developing economies have underdeveloped futures markets and financial markets. Although the modern risk-management instruments are accessible to traders all around the world, most traders in developing countries are unable to access this advantage because of a variety of institutional imperfections and financial constraints.

Table 24: Fixed Effects Panel Regression Results (Disaggregated)

	Full sample			Advanced economies			Emerging economies		
	Agri.	**Chem. & mach.**	**Manuf.**	**Agri.**	**Chem. & mach.**	**Manuf.**	**Agri.**	**Chem. & mach.**	**Manuf.**
Log (volatility)	0.088	-0.262*	-0.239*	0.638*	-0.064	-0.416	-0.069	-0.361**	-0.215*
	(0.115)	(0.132)	(0.140)	(0.286)	(0.541)	(0.365)	(0.098)	(0.126)	(0.110)
Square of log (volatility)	-0.013	0.058**	0.067**	-0.120*	0.008	0.099	0.016	0.081**	0.058**
	(0.024)	(0.027)	(0.028)	(0.062)	(0.108)	(0.076)	(0.025)	(0.030)	(0.024)
Lag [log (GDP)]	0.116	0.509***	0.230***	0.050	0.587***	0.449**	0.079	0.520***	0.227**
	(0.127)	(0.080)	(0.078)	(0.088)	(0.130)	(0.140)	(0.166)	(0.130)	(0.092)
Lag [log (USGDP)]	0.565	0.984***	0.862***	0.558	0.674	0.643	0.668	1.377**	0.447
	(0.354)	(0.286)	(0.260)	(0.436)	(0.443)	(0.493)	(0.485)	(0.418)	(0.281)
Log (population)	2.209*	-1.693*	0.133	1.158	-1.281	-0.628	3.421**	-3.106*	1.125*
	(1.124)	(0.936)	(0.443)	(0.710)	(1.054)	(0.433)	(1.066)	(1.405)	(0.515)
Log (U.S. population)	21.835	-6.959	-1.256	22.779	-10.217	3.428	19.455	7.877	-5.670
	(14.3)	(9.698)	(10.036)	(19.614)	(10.329)	(15.018)	(20.828)	(8.394)	(11.928)
FTA	0.022	0.084	0.078	0.181	0.022	0.144	-0.19**	0.177	-0.027
	(0.128)	(0.077)	(0.074)	(0.102)	(0.076)	(0.093)	(0.063)	(0.135)	(0.058)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-128.7	39.26	4.780	-129.8	59.05	-18.33	-122.1	-43.53	31.90
	(81.78)	(56.01)	(55.17)	(112.2)	(55.57)	(80.59)	(116.8)	(51.46)	(65.68)
Adjusted *R*-squared	0.376	0.280	0.324	0.298	0.209	0.415	0.531	0.428	0.391
No. of observations	2670	2670	2670	1403	1403	1403	1267	1267	1267

Note. Standard errors are in the parentheses. Significance of estimates at 0.01, 0.05, 0.10 are marked as ***, **, & *, respectively. Year dummies and month dummies were included in each specification to capture trend effects and seasonal effects in trade, respectively. Complete results are reported in the appendix.

We also examine the trade effects of exchange rate volatilities using a conventional volatility measure-standard deviation of daily bilateral exchange rate-for the same period of time. We also include all control variables used in earlier specifications for the implied options volatility. Table 25 and 26 present the results of a new specification that includes the standard deviation of exchange rates. The results show that, contrary to our main results, the historical exchange rate volatility increases the trade volume between partner countries. The positive trade effects of exchange rate volatility are weak for the complete sample. For the samples of the advanced economies and the emerging economies, the coefficients are, however,

statistically significant at the convention 5 percent level. The coefficients of the other control variables have come out as in earlier models in terms of signs and magnitude.

Table 26 reports the sectoral level estimations using the historical volatility measure-standard deviation of the bilateral exchange rate. The results show that, for complete sample, exchange rate variabilities matter for the trade volume of chemical and machinery, but do not matter for the agriculture and the manufacturing trade. We observe concavity in the relationship between the chemical & machinery trade and the exchange rate volatility as the square of the historical volatility measure appears statistically significant with a negative sign, while the level of the volatility measure appears statistically significant with a positive sign. The results for the sample of the advanced economies show, however, the exchange rate volatilities increase trade volume for all sectors. The link between the exchange rate volatilities and the trade volumes, however, are weak. For the sample of emerging economies, the exchange rate volatilities only help the agricultural trade and the positive link is statistically significant at the conventional 5 percent level.

The positive trade effects of historical exchange rate volatilities are not anew in the literature. Viaene and Vries (1991) have shown that the positive trade effects of exchange rate volatilities may be consistent with the theories given the presence of the forward market for currencies. McKenzie and Brooks (1997) also find positive trade effects of exchange rate volatility for the US-German trade over the period of 1973-1992. Peter et. al. (2004) find that the negative relationship between the exchange rate volatility and trade is not robust when the bilateral trade is modeled over the exchange rate volatilities along with other covariates.

However, the standard deviation of the exchange rate is a *backward*-looking measure of exchange rate volatility, and trade is affected by *future* exchange rate uncertainties. Thus, the results from the model using a new measure of forward-looking exchange rate volatilities-foreign exchange options implied volatility-are more reliable. Day & Lewis (1992) and Poon & Granger (2005) have shown, for stock options and financial asset returns, that implied volatility contains additional information over historical volatility measures.

Table 25: Fixed Effects Panel Regression Results with Historical Volatility (Total Trade)

	Full Sample	**Advanced Economies**	**Emerging Economies**
Standard Deviation of Bilateral Exchange Rates	0.004*	0.005**	0.006**
	(0.002)	(0.002)	(0.002)
Square of Standard Deviation of Bilateral Exchange Rates	-0.000	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)
Lag [Log (GDP)]	0.473***	0.432***	0.446***
	(0.080)	(0.107)	(0.131)
Lag[Log (USGDP)]	0.864***	0.900***	1.052***
	(0.195)	(0.267)	(0.269)
Log(population)	-1.172	-0.506	-1.910
	(0.679)	(0.527)	(1.357)
log (US Population)	-5.297	-9.941	8.101
	(8.382)	(6.641)	(12.472)
FTA	0.214	0.092	0.383*
	(0.128)	(0.069)	(0.178)
Country Fixed Effects	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Constant	30.472	53.968	-43.823
	(47.547)	(37.147)	(70.722)
R-squared (Within)	0.399	0.395	0.483
R-squared (Between)	0.310	0.236	0.456
R-squared (Overall)	0.285	0.217	0.371
No. of Observations	2670	1403	1267

Notes: 1. Standard Errors are in the parentheses. Significance of estimates at 0.01, 0.05, 0.10 is marked as ***, **, & * respectively. 2. Year dummies and month dummies were included in each specification to capture trend effects and seasonal effects in trade respectively. Complete results are reported in the appendix.

Table 26: Fixed Effects Panel Regression Results with Historical Volatility Disaggregated)

	Full Sample			Advanced Economies			Emerging Economies		
	Agri.	**Chem. & Mach.**	**Manuf.**	**Agri.**	**Chem. & Mach.**	**Manuf.**	**Agri.**	**Chem. & Mach.**	**Manuf.**
Standard Deviation of Bilateral Exchange Rates	0.004	0.009***	-0.001	0.005*	0.004*	0.006*	0.004**	0.003	0.004
	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Square of Standard Deviation of Bilateral Exchange Rates	-0.000	-0.000***	0.000	-0.000	-0.000*	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lag [Log (GDP)]	0.113	0.061	0.074	0.509***	0.597***	0.511***	0.205**	0.443**	0.202*
	(0.131)	(0.079)	(0.170)	(0.083)	(0.122)	(0.142)	(0.085)	(0.150)	(0.100)
Lag [Log (USGDP)]	0.545	0.414	0.569	0.863***	0.689*	1.064**	0.514**	0.482	0.031
	(0.348)	(0.439)	(0.516)	(0.265)	(0.364)	(0.432)	(0.236)	(0.464)	(0.199)
Log(population)	2.254*	1.475*	3.443**	-1.769*	-1.351	-3.073*	0.156	-0.784	1.251**
	(1.111)	(0.785)	(1.074)	(0.944)	(1.121)	(1.451)	(0.424)	(0.468)	(0.513)
log (US Population)	23.010	29.030	20.181	-6.508	-11.948	9.239	3.863	5.732	-1.657
	(13.56)	(18.009)	(19.427)	(9.538)	(9.422)	(8.588)	(9.518)	(14.931)	(9.391)
FTA	0.033	0.213*	-0.195**	0.089	0.017	0.203	0.082	0.136	-0.023
	(0.132)	(0.110)	(0.064)	(0.084)	(0.085)	(0.140)	(0.074)	(0.091)	(0.055)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-135.05	-163.117	-124.833	38.497	68.555	-46.921	-18.791	-28.760	15.158
	(78.09)	(103.987)	(110.737)	(55.225)	(52.577)	(51.589)	(52.964)	(80.802)	(54.580)
R-squared (Within)	0.384	0.311	0.543	0.285	0.227	0.430	0.313	0.421	0.386
R-squared (Between)	0.457	0.687	0.131	0.335	0.674	0.308	0.559	0.588	0.440
R-squared (Overall)	0.458	0.660	0.139	0.326	0.668	0.231	0.565	0.545	0.394
No. of Observations	2670	1403	1267	2670	1403	1267	2670	1403	1267

Notes: 1. Standard Errors are in the parentheses. Significance of estimates at 0.01, 0.05, 0.10 is marked as ***, **, & * respectively.
2. Year dummies and month dummies were included in each specification to capture trend effects and seasonal effects in trade respectively. Complete results are reported in the appendix.

3.6. Concluding Remarks

The chapter examines the trade effects of exchange rate volatilities using a novel and superior measure of exchange rate volatility. While the use of models based on time series,

which are backward-looking measures of exchange rate volatility, is common practice in the literature, this study instead uses a forward-looking measure of exchange rate volatility, foreign exchange options implied volatility, to evaluate the impact of exchange rate volatility on trade flows. Using a panel fixed-effects model to analyze the monthly data for the major United States trade partner countries, the study finds that there are moderate adverse effects of exchange rate volatilities on trade volume. The significance of the negative trade effects of exchange rate volatilities disappears when the sample includes only the advanced economies; the adverse effect of exchange rate volatilities on trade volume is, however, statistically significant for the sample that includes only the trading partners from emerging economies.

The negative trade effects of exchange rate volatilities are strong for trade in the chemical & machinery and manufacturing sectors. For advanced economies, agricultural trade was firmly hurt by the exchange rate volatilities, while the trade in the chemical & machinery and manufacturing sectors are not significantly affected. The scenarios are reversed in the sample of emerging economies. For this group of countries, agricultural trade is not affected by the exchange rate volatilities, but trade in the chemical & machinery and manufacturing sectors is significantly affected by exchange rate volatilities.

The results of this study imply that traders in the advanced economies are capable of hedging their risk by using different risk management tools, such as futures, options, etc; traders in countries with emerging economies often have no access to these risk management tools and thus these markets are more significantly affected by exchange rate uncertainties.

3.7. References

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APPENDICES

Appendix A: Appendix to the Chapter 1

Table A1 :Linear Probability Model (LPM) and Probit Model (Including CRE Variables)

	LPM		**Probit model**	
	Coeff.	***SE***	**Mar. Eff.**	***SE***
Mechanized (yes = 1)	0.090***	(0.028)	0.255***	(0.083)
Age of household head	-0.001	(0.002)	-0.004	(0.006)
Household size	0.021***	(0.008)	0.062***	(0.023)
Labor endowment dummies (ref: single working member)				
Two adult workers	0.081**	(0.035)	0.217**	(0.103)
Three adult workers	0.132**	(0.059)	0.342**	(0.167)
Female participation in labor force (yes = 1)	0.088*	(0.048)	0.240*	(0.141)
Log (total schooling years of workers)	0.010	(0.007)	0.028	(0.020)
Land endowment dummies (ref: marginal landowner (<0.4 Ha))				
Small landowner (> = 0.4 Ha & <1.0 Ha)	-0.008	(0.036)	-0.013	(0.099)
Medium landowner (> = 1.0 Ha & <2.0 Ha)	0.020	(0.048)	0.059	(0.129)
Large landowner (> = 2.0 Ha)	0.120*	(0.068)	0.347*	(0.184)
NGO membership (yes = 1)	0.123***	(0.028)	0.340***	(0.074)
Log (gross margin of farming in 2008 Tk.)	0.004	(0.015)	0.009	(0.038)
Fragmentation index	-0.081	(0.068)	-0.224	(0.213)
Cropping intensity	0.023	(0.042)	0.061	(0.117)
Year dummy (2008 = 1)	-0.080***	(0.027)	-0.223***	(0.077)
Correlated effects variables (group means of the variables)				
Age of household head	-0.001	(0.003)	-0.002	(0.007)
Household size	-0.077	(0.055)	-0.225	(0.160)
Total adult workers	0.048*	(0.027)	0.139*	(0.081)
Log (total schooling years of workers)	0.012	(0.008)	0.035	(0.022)
Log (total landownership)	-0.028*	(0.015)	-0.085**	(0.041)
Log (gross margin of farming in 2008 Tk.)	-0.033*	(0.019)	-0.092*	(0.054)
Fragmentation index	-0.068	(0.085)	-0.180	(0.252)
Cropping intensity	0.040	(0.051)	0.122	(0.135)
Constant	0.518***	(0.092)	0.080	(0.281)
Wald chi2(21)	289.4***		206.7***	
R-squared	0.11		0.084	
Observations	1691			

Table A2: Bivariate Probit Marginal Effects Estimates (Including CRE Variables)

	Bivariate Probit model			
	Non-farm participation equation		**Mechanization equation**	
	Marr. Eff.	***SE***	**Marr. Eff.**	***SE***
Mechanized (yes = 1)	0.349***	(0.101)		
Age of household head	-0.001	(0.002)	-0.001	(0.002)
Household size	0.018**	(0.008)	0.008	(0.006)
Labor endowment dummies (ref: single working member)				
Two adult workers	0.081**	(0.033)	-0.046	(0.030)
Three adult workers	0.122**	(0.055)	-0.045	(0.047)
Female participation in labor force (yes = 1)	0.077*	(0.046)	0.018	(0.039)
Log (total schooling years of workers)	0.011*	(0.006)	-0.006	(0.006)
Land endowment dummies (ref: marginal landowner (<0.4 Ha))				
Small landowner (> = 0.4 Ha & <1.0 Ha)	-0.009	(0.034)	0.028	(0.030)
Medium landowner (> = 1.0 Ha & <2.0 Ha)	0.020	(0.043)	0.014	(0.038)
Large landowner (> = 2.0 Ha)	0.101	(0.061)	0.077	(0.054)
NGO membership (yes = 1)	0.108***	(0.025)	-0.013	(0.021)
Log (gross margin of farming in 2008 Tk.)	0.005	(0.013)	-0.002	(0.012)
Fragmentation index	-0.106	(0.067)	0.103	(0.063)
Cropping intensity	0.015	(0.037)	0.021	(0.034)
Year dummy (2008 = 1)	-0.141***	(0.033)	0.234***	(0.021)
Correlated effects variables (group means of the variables)				
Age of household head	-0.001	(0.002)	-0.000	(0.002)
Household size	-0.079	(0.053)	0.046	(0.046)
Total adult workers	0.049*	(0.026)	-0.003	(0.022)
Log (total schooling years of workers)	0.010	(0.007)	0.003	(0.006)
Log (total landownership)	-0.031**	(0.014)	0.007	(0.012)
Log (gross margin of farming in 2008 Tk.)	-0.032*	(0.017)	-0.004	(0.014)
Fragmentation Index	-0.026	(0.085)	-0.139*	(0.076)
Cropping Intensity	0.018	(0.045)	0.088**	(0.040)
Instrument variables				
Log (mean rainfall in mm in last ten years)			-0.298***	(0.046)
Any cultivated land with clay loam soil? (yes = 1)			0.045**	(0.021)
Any cultivated land with very high elevation? (yes = 1)			-0.039**	(0.020)
/athrho	-0.53**	(0.27)		
rho	-0.48	(0.21)		
Wald test of rho = 0: chi2(1)	3.83**			
Murphy's score test for biprobit chi2(9) =	6.01 (*p*-val = 0.74)			
Average treatment effects (ATE)	0.33**	(0.099)		
Average treatment effects on the treated (ATT)	0.31***	(0.089)		
Observations	1691			

Table A3: Endogenous switching probit estimates (including CRE variables)

	Endogenous SPM					
	Mechanized households		Non-mechanized households		Mechanization equation	
	Coeff.	***SE***	**Coeff.**	***SE***	**Coeff.**	***SE***
Age of household head	0.003	(0.007)	-0.018	(0.013)	-0.003	(0.006)
Household size	0.033	(0.025)	0.155**	(0.064)	0.027	(0.025)
Labor endowment dummies (ref: single working member)						
Two adult workers	0.253**	(0.108)	0.147	(0.203)	-0.176	(0.120)
Three adult workers	0.421**	(0.178)	-0.062	(0.331)	-0.162	(0.183)
Female participation in labor force (yes = 1)	0.170	(0.153)	0.575	(0.355)	0.052	(0.158)
Log (total schooling years of workers)	0.033*	(0.019)	0.041	(0.042)	-0.024	(0.021)
Land endowment dummies (ref: marginal landowner (<0.4 Ha))						
Small landowner (> = 0.4 Ha & <1.0 Ha)	-0.019	(0.115)	-0.105	(0.216)	0.113	(0.125)
Medium landowner (> = 1.0 Ha & <2.0 Ha)	0.052	(0.158)	-0.005	(0.264)	0.057	(0.150)
Large landowner (> = 2.0 Ha)	0.296	(0.221)	0.372	(0.410)	0.294	(0.208)
NGO membership (yes = 1)	0.355***	(0.083)	0.179	(0.149)	-0.044	(0.091)
Log (gross margin of farming in 2008 Tk.)	0.004	(0.039)	-0.005	(0.094)	-0.008	(0.043)
Fragmentation Index	-0.384*	(0.233)	-0.047	(0.400)	0.390*	(0.225)
Cropping intensity	0.037	(0.109)	0.020	(0.244)	0.082	(0.132)
Year dummy (2008 = 1)	-0.426***	(0.117)	-0.481	(0.309)	0.898***	(0.079)
Correlated effects variables (group means of the variables)						
Age of household head	-0.002	(0.008)	-0.006	(0.014)	-0.000	(0.007)
Household size	-0.143	(0.171)	-0.637*	(0.370)	0.195	(0.190)
Total adult workers	0.081	(0.088)	0.454***	(0.168)	-0.022	(0.087)
Log (total schooling years of workers)	0.033	(0.023)	0.004	(0.047)	0.011	(0.025)
Log (total landownership)	-0.103**	(0.052)	-0.045	(0.077)	0.023	(0.050)
Log (gross margin of farming in 2008 Tk.)	-0.054	(0.055)	-0.277**	(0.130)	-0.009	(0.056)
Fragmentation index	-0.024	(0.299)	-0.343	(0.527)	-0.527*	(0.282)
Cropping intensity	-0.009	(0.142)	0.533*	(0.317)	0.322**	(0.161)
Instrument variables						
Log (mean rainfall in mm in last ten years)					-1.157***	(0.204)
Any cultivated land with clay loam soil? (yes = 1)					0.170*	(0.090)
Any cultivated land with very high elevation? (yes = 1)					-0.152*	(0.084)
Constant	0.702*	(0.389)	0.107	(0.604)	7.984***	(1.533)
/athrho1	-0.575	(2.409)				
/athrho0	-0.490	(3.590)				
rho1	-0.52	(1.76)				
rho0	-0.45	(2.85)				
Wald test if indep. eqns. (rho1 = rho2 = 0) Chi2			4.8* (*p*-val = 0.09)			
Observations	1691					
Average treatment effects (ATE)	0.31					
Average treatment effects on the treated (ATT)	0.28					
Wald chi2(23)	241.55***					
Observations	1691					

Note. Standard errors in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Linear Regression Model of Labor Supply (Including CRE Variables)

Dependent Variable: Number of Days household members worked off-farm in previous 12 months	**Non-farm labor supply equation**	
	Coeff.	***SE***
Mechanized (yes = 1)	23.790**	(9.260)
Age of household head	-0.298	(0.799)
Household size	3.750	(2.918)
Labor endowment dummies (ref: single working member)		
Two adult workers	37.128***	(12.723)
Three plus adult workers	87.527***	(21.861)
Female participation in labor force (yes = 1)	22.229	(18.830)
Log (total schooling years of workers)	3.661*	(1.937)
Land endowment dummies (ref: marginal landowner (<0.4 Ha))		
Small landowner (> = 0.4 Ha & <1.0 Ha)	0.415	(11.922)
Medium landowner (> = 1.0 Ha & <2.0 Ha)	-4.837	(15.814)
Large landowner (> = 2.0 Ha)	28.082	(24.283)
NGO membership (yes = 1)	32.485***	(8.493)
Log (gross margin of farming in 2008 Tk.)	-0.071	(4.750)
Fragmentation index	-59.365**	(23.835)
Cropping intensity	-0.186	(12.787)
Year dummy (2008 = 1)	-1.448	(8.891)
Correlated effects variables (group means of the variables)		
Age of household head	0.292	(0.963)
Household size	-2.680	(18.425)
Total adult workers	10.235	(10.416)
Log (total schooling years of workers)	6.116***	(2.294)
Log (total landownership)	-4.836	(4.801)
Log (gross margin of farming in 2008 Tk.)	-7.904	(6.677)
Fragmentation index	-22.662	(30.109)
Cropping intensity	22.831	(16.224)
Constant	87.174***	(31.932)
F(21, 1669)	12.62 (*p*-val = 0.000)	
R-squared	0.15	
Observations	1691	

Table A5: Endogenous Treatment Effects Model (Including CRE Variables)

	ETE model			
Log (non-farm workdays)	**Non-farm labor supply equation**		**Mechanization equation**	
	Coeff.	***SE***	**Coeff.**	***SE***
Mechanized (yes = 1)	64.140**	(30.845)		
Age of household head	-0.264	(0.797)	-0.004	(0.007)
Household size	3.411	(2.956)	0.031	(0.025)
Labor endowment dummies (ref: single working member)				
Two adult workers	38.842***	(12.800)	-0.174	(0.115)
Three adult workers	89.438***	(22.100)	-0.160	(0.183)
Female participation in labor force (yes = 1)	22.062	(18.821)	0.056	(0.150)
Log (total schooling years of workers)	3.926**	(1.947)	-0.023	(0.022)
Land endowment dummies (ref: marginal landowner (<0.4 Ha))				
Small landowner (> = 0.4 Ha & <1.0 Ha)	-0.350	(11.957)	0.117	(0.115)
Medium landowner (> = 1.0 Ha & <2.0 Ha)	-4.668	(15.860)	0.068	(0.146)
Large landowner (> = 2.0 Ha)	26.418	(24.290)	0.301	(0.207)
NGO membership (yes = 1)	32.272***	(8.458)	-0.054	(0.083)
Log (gross margin of farming in 2008 Tk.)	0.173	(4.774)	-0.003	(0.046)
Fragmentation index	-64.14***	(23.866)	0.405*	(0.245)
Cropping intensity	-0.709	(12.728)	0.065	(0.131)
Year dummy (2008 = 1)	-11.620	(10.809)	0.905***	(0.087)
Correlated effects variables (group means of the variables)				
Age of household head	0.280	(0.962)	0.001	(0.008)
Household size	-3.591	(18.481)	0.191	(0.177)
Total adult workers	10.741	(10.484)	-0.024	(0.086)
Log (total schooling years of workers)	5.939***	(2.296)	0.010	(0.024)
Log (total landownership)	-5.268	(4.836)	0.021	(0.046)
Log (gross margin of farming in 2008 Tk.)	-8.282	(6.693)	-0.015	(0.054)
Fragmentation index	-18.247	(30.102)	-0.546*	(0.292)
Cropping intensity	19.565	(16.258)	0.349**	(0.153)
Instrument variables				
Log (mean rainfall in mm in last ten years)			-1.176***	(0.184)
Any cultivated land with clay loam soil? (yes = 1)			0.142*	(0.084)
Any cultivated land with very high elevation? (yes = 1)			-0.158**	(0.077)
Constant	70.886**	(34.452)	8.118***	(1.384)
Log likelihood	-11737			
Observation	1691			
/athrho	-0.16	(0.11)		
/lnsigma	5.06***	(0.025)		
rho	-0.15	(0.10)		
sigma	158.3	(3.92)		
lambda	-24.37	(16.6)		
Wald test of indep. eqns. (rho = 0): chi2(1) =	1.03 (*p*-val = 0.31)			

Table A6 : Endogenous Treatment Effects Model (Robustness Check excluding top 10%)

Log (non-farm workdays)	**Non-farm labor supply equation**		**Mechanization equation**	
	Coeff.	***SE***	**Coeff.**	***SE***
Mechanized (yes = 1)	56.690***	(19.727)		
Age of household head	-0.594	(0.571)	-0.003	(0.008)
Household size	1.019	(1.924)	0.042	(0.026)
Labor endowment dummies (ref: single working member)				
Two adult workers	18.909*	(9.670)	-0.115	(0.125)
Three adult workers	31.682**	(16.100)	-0.178	(0.199)
Female participation in labor force (yes = 1)	30.943**	(14.678)	0.178	(0.166)
Log (total schooling years of workers)	3.306**	(1.550)	-0.023	(0.022)
Land endowment dummies (ref: marginal landowner (<0.4 Ha))				
Small landowner (> = 0.4 Ha & <1.0 Ha)	0.403	(8.970)	0.110	(0.121)
Medium landowner (> = 1.0 Ha & <2.0 Ha)	11.929	(11.937)	0.107	(0.152)
Large landowner (> = 2.0 Ha)	29.821*	(17.184)	0.261	(0.218)
NGO membership (yes = 1)	25.413***	(6.512)	-0.087	(0.086)
Log (gross margin of farming in 2008 Tk.)	3.789	(3.656)	-0.007	(0.048)
Fragmentation index	-21.213	(18.875)	0.416	(0.257)
Cropping intensity	-6.891	(10.015)	0.032	(0.138)
Year dummy (2008 = 1)	-12.941*	(7.722)	0.89***	(0.091)
Correlated effects variables (group means of the variables)				
Age of household head	0.580	(0.668)	-0.003	(0.008)
Household size	-11.345	(13.248)	0.124	(0.185)
Total adult workers	6.699	(7.901)	-0.028	(0.095)
Log (total schooling years of workers)	2.491	(1.801)	0.009	(0.025)
Log (total landownership)	-7.266**	(3.586)	0.017	(0.048)
Log (gross margin of farming in 2008 Tk.)	-9.420*	(4.942)	-0.028	(0.058)
Fragmentation index	-25.533	(23.249)	-0.565*	(0.309)
Cropping intensity	15.763	(12.425)	0.396**	(0.163)
Instrument variables				
Log (mean rainfall in mm in last ten years)			-1.19***	(0.193)
Any cultivated land with clay loam soil? (yes = 1)			0.166*	(0.088)
Any cultivated land with very high elevation? (yes = 1)			-0.134*	(0.080)
Constant	82.461***	(26.093)	8.38***	(1.452)
Log likelihood	-10006.7			
Observation	1691			
/athrho	-0.19**	(0.09)		
/lnsigma	4.71***	(0.018)		
rho	-0.19	(0.09)		
sigma	111.6	(2.09)		
lambda	-21.00	(10.41)		
Wald test of indep. eqns. (rho = 0): chi2(1) =	1.15 (*p*-val = 0.25)			

Appendix B: Appendix to Chapter 2

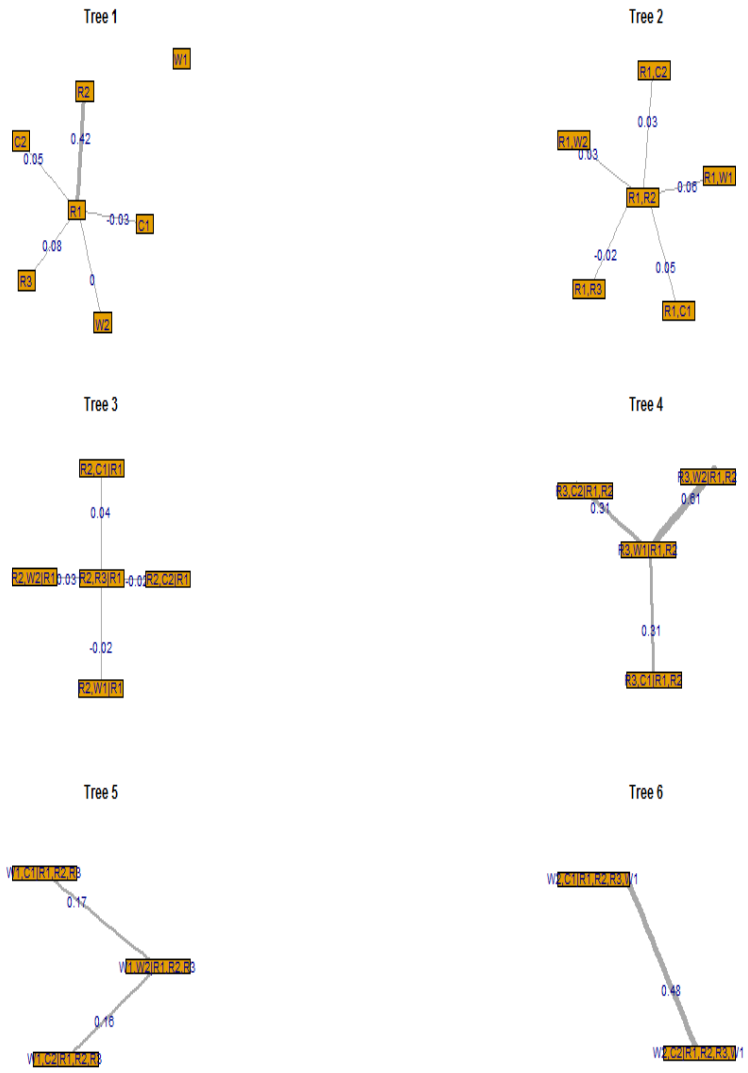

Figure B1. C-vine tree plots among the market pairs.

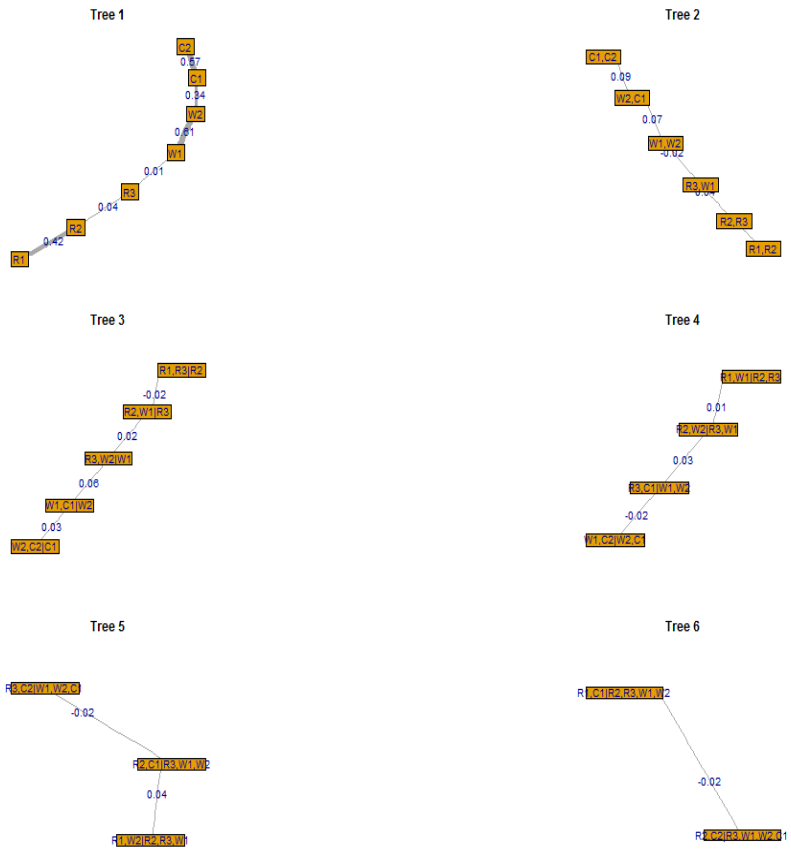

Figure B2. D-vine tree plots among the market pairs.

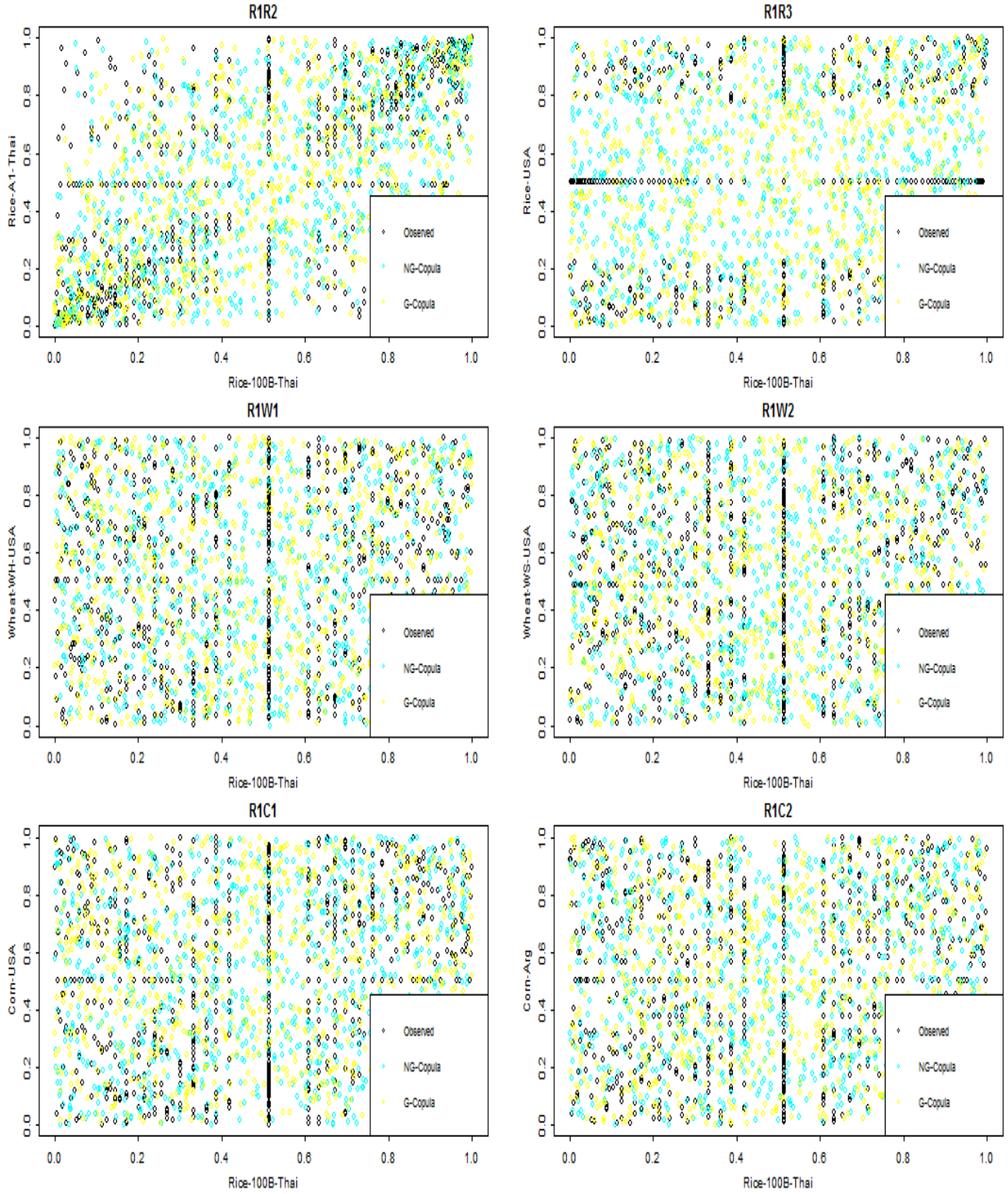

Figure B3. Observed and simulated data are plotted (using bivariate copulas)

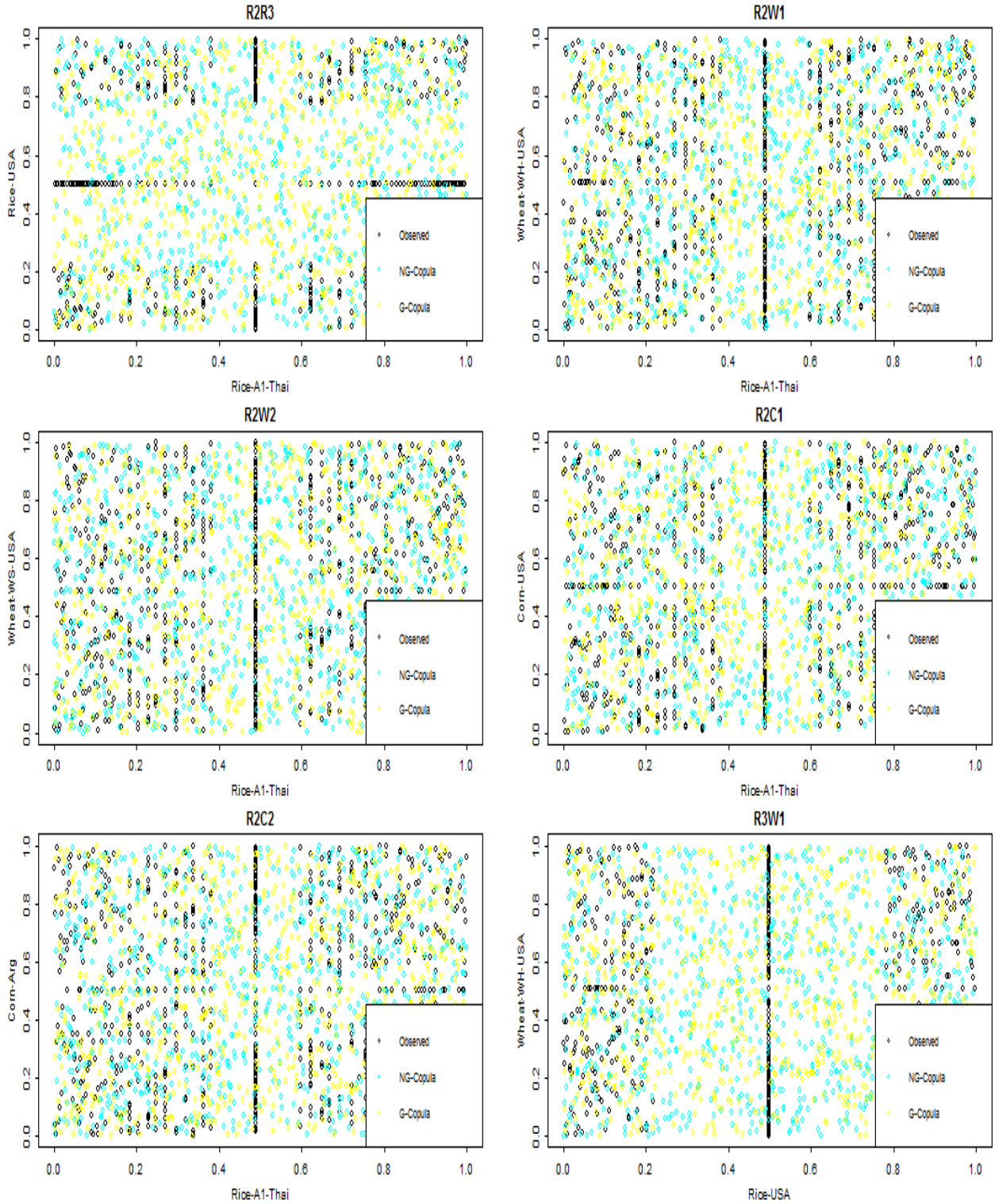

Figure B3 (continued)

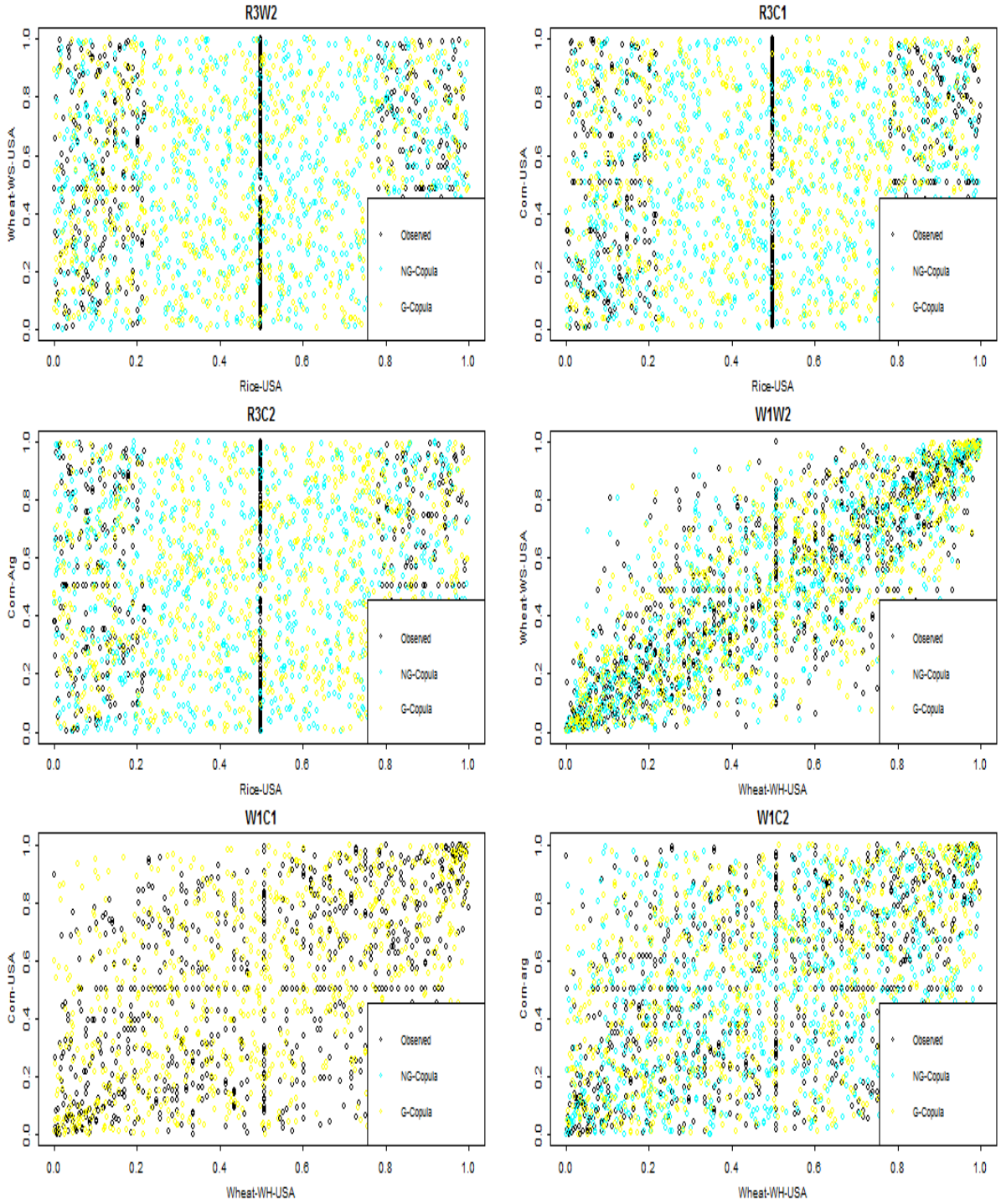

Figure B3 (continued)

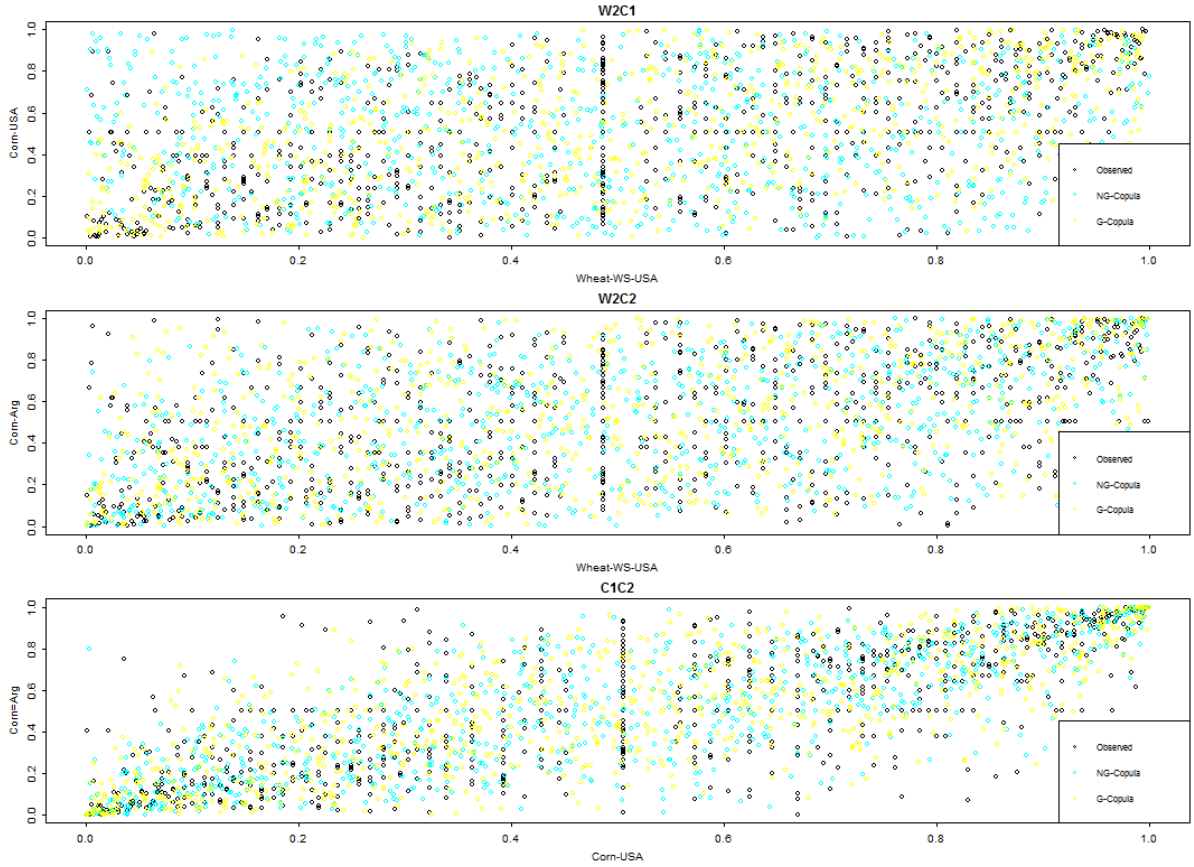

Figure B3 (continued)

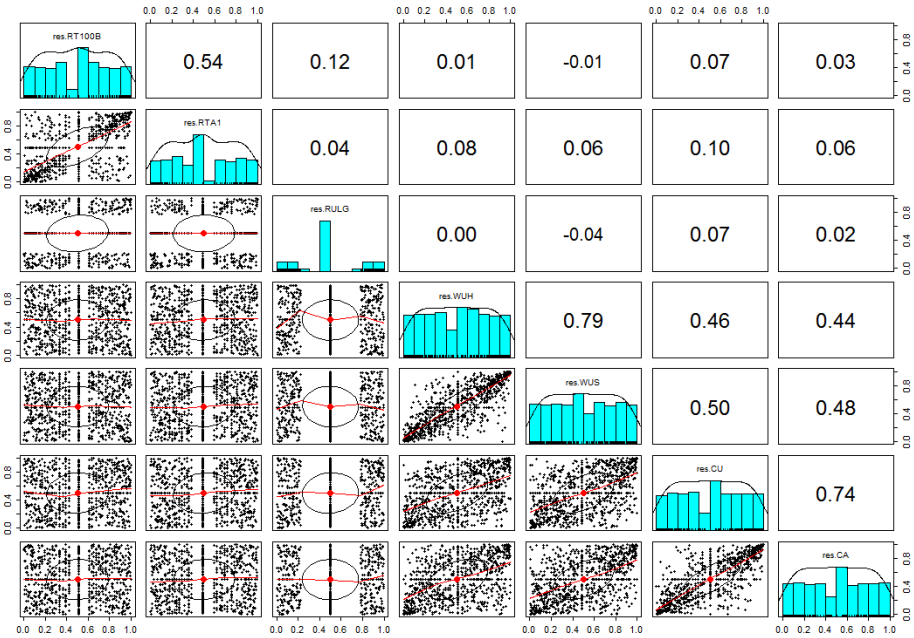

Figure B4. Original uniform CDFs data.

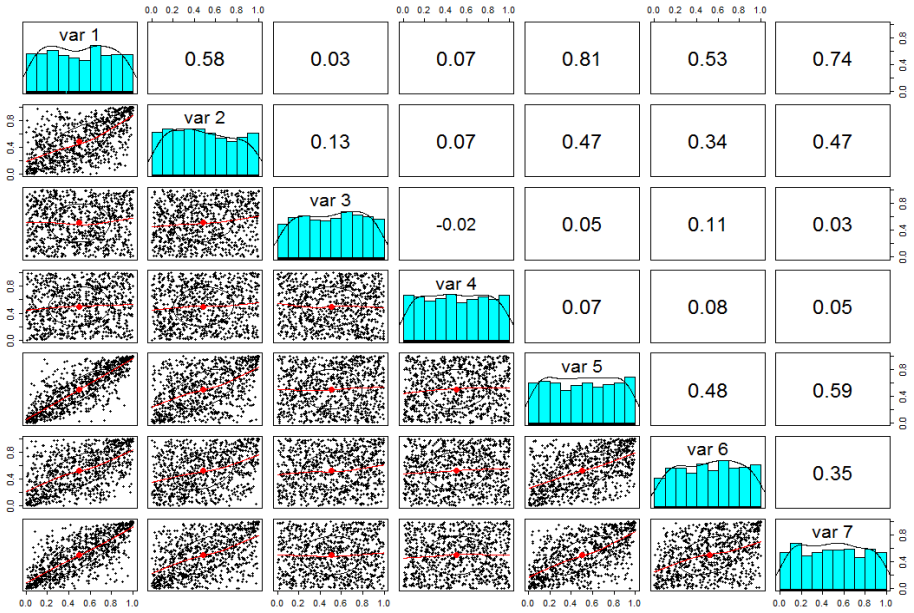

Figure B5. Simulated data from C-Vine copulas.

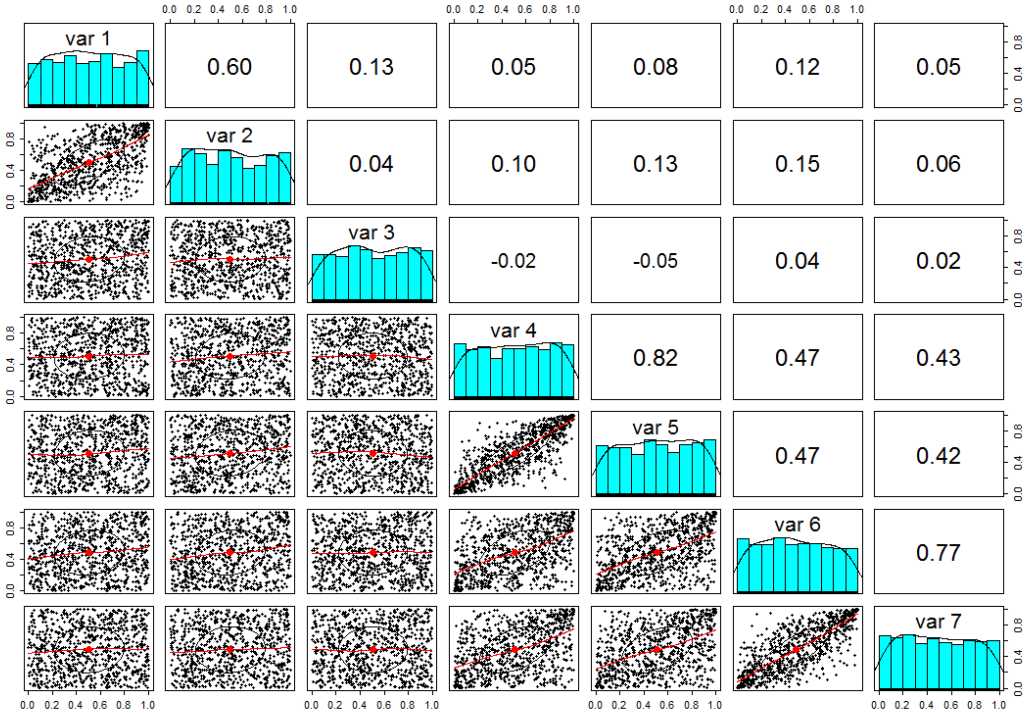

Figure B6, Simulated data from D-Vine copulas.

Appendix C: Appendix to the Chapter 3

Table C1 : Hausman Test: Fixed vs. Random (Quarterly Data)

Dependent variables	chi2(df)	Prob>chi2
Total trade	chi2(7) = 111.4	0.00
Agriculture	chi2(7) = 23.60	0.00
Chemical & machinery	chi2(7) = 101.17	0.00
Manufacturing	chi2(10) = 253.5	0.00

H0: Random-effects model is preferred. Ha: Fixed-effects model is preferred

Table C2: Fixed Effects Panel Regression Results (Quarterly Data)

	Full Sample	Advanced Economies	Emerging Economies
Log (Volatility)	-0.161	0.198	-0.270*
	(0.132)	(0.249)	(0.161)
Square Of Log (Volatility)	0.036	-0.035	0.059
	(0.027)	(0.051)	(0.035)
Lag[Log (GDP)]	0.609***	0.476***	0.545***
	(0.082)	(0.130)	(0.150)
Lag[Log (USGDP)]	0.497	0.940	0.705
	(0.544)	(0.563)	(0.815)
Log(population)	-1.621**	-0.808	-2.336
	(0.676)	(0.655)	(1.541)
log (US Population)	0.666	0.726	-1.566
	(3.150)	(4.365)	(5.297)
FTA	0.255**	0.082	0.470***
	(0.101)	(0.059)	(0.071)
Quarter Dummies			
Q2	0.071***	0.055***	0.084**
	(0.013)	(0.009)	(0.026)
Q3	0.051**	0.001	0.107***
	(0.021)	(0.020)	(0.028)
Q4	0.073***	0.046***	0.095**
	(0.016)	(0.012)	(0.031)
Country Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Constant	-4.488	-13.931	9.422
	(10.662)	(15.687)	(17.213)
Observations	900	472	428
Adjusted R-squared	0.764	0.736	0.816

Note. Standard errors are in parentheses. * p<0.10, ** p<0.05 & *** p<0.01

Table C3: Fixed Effects Panel Regression Results: Disaggregated (Quarterly Data)

	Full Sample			Advanced Economies			Emerging Economies		
	Agri.	Chem. & Mach.	Man.	Agri.	Chem. & Mach.	Man.	Agri.	Chem. & Mach.	Man.
Log (Volatility)	0.117	-0.216	-0.167	0.556	0.181	-0.314	-0.046	-0.360*	-0.114
	(0.115)	(0.173)	(0.159)	(0.396)	(0.543)	(0.429)	(0.093)	(0.186)	(0.154)
Square Of Log (Volatility)	-0.013	0.046	0.054	-0.094	-0.057	0.080	0.017	0.085*	0.039
	(0.025)	(0.036)	(0.032)	(0.091)	(0.107)	(0.088)	(0.030)	(0.042)	(0.032)
Lag[Log (GDP)]	0.26**	0.622***	0.362***	0.104	0.641**	0.531**	0.212	0.594***	0.349**
	(0.109)	(0.087)	(0.113)	(0.146)	(0.194)	(0.166)	(0.151)	(0.165)	(0.123)
Lag[Log (USGDP)]	-0.243	0.587	2.778***	0.080	0.378	1.615**	0.100	0.861	3.633***
	(0.595)	(0.475)	(0.448)	(0.871)	(0.848)	(0.501)	(1.012)	(0.876)	(0.585)
Log(population)	1.653	-2.139**	-0.333	0.999	-1.562	-0.990*	2.811**	-3.497*	0.593
	(1.071)	(0.946)	(0.463)	(0.838)	(1.261)	(0.479)	(0.985)	(1.655)	(0.511)
log (US Population)	3.490	-0.595	-13.196***	4.925	1.505	-5.677**	-1.724	-1.644	-21.773***
	(5.487)	(3.101)	(2.989)	(7.163)	(5.426)	(2.386)	(9.287)	(6.495)	(4.862)
FTA	0.033	0.120*	0.134	0.152	0.016	0.142	-0.118**	0.273**	0.107
	(0.115)	(0.061)	(0.078)	(0.108)	(0.076)	(0.094)	(0.050)	(0.083)	(0.145)
Quarter Dummies									
Q2	-0.042	0.075***	0.070***	-0.048	0.046***	0.065***	-0.037	0.104***	0.079**
	(0.035)	(0.018)	(0.013)	(0.044)	(0.013)	(0.011)	(0.059)	(0.030)	(0.027)
Q3	-0.014	0.053*	0.092***	-0.009	-0.011	0.039**	-0.013	0.120***	0.153***
	(0.051)	(0.025)	(0.022)	(0.045)	(0.027)	(0.016)	(0.099)	(0.033)	(0.031)
Q4	0.059	0.086***	0.051***	0.083	0.046***	0.041*	0.024	0.132***	0.065**
	(0.051)	(0.018)	(0.013)	(0.047)	(0.012)	(0.018)	(0.098)	(0.029)	(0.025)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-19.17	2.341	33.863**	-28.408	-9.465	10.090	0.064	10.859	64.978**
	(22.94)	(12.599)	(12.182)	(28.64)	(17.628)	(8.666)	(39.94)	(24.946)	(22.314)
Adjusted R-squared	0.698	0.622	0.681	0.655	0.509	0.754	0.765	0.731	0.653
Observations	900	900	900	472	472	472	428	428	428

Note. Standard errors are in parentheses * $p < 0.10$, ** $p < 0.05$ & *** $p < 0.01$