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by

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Examining the Risk-Return Relationship between Agribusiness Stocks and the Market

Volatility and the trade-off between risk and returns have been considered key components of finance theory at least since Merton's intertemporal capital asset pricing model (ICAPM, 1973). In this study, we employ several bivariate GARCH-M models to investigate Merton's ICAPM for agribusiness industries and examine the best specification to use in estimating the relationship of asset returns in these industries with the broader market. The expected positive relation between stock return and its risk holds for both industries and we found a high posterior probability of a positive tradeoff for the agricultural production portfolio.

Keywords : Asset pricing; Bayesian econometrics; Bivariate GARCH-M; Risk return trade-off

Introduction

The idea that investors expect higher returns in exchange for holding riskier assets has been widely accepted throughout economics and finance. This was formalized by Merton (1973) in his intertemporal capital asset pricing model (ICAPM). Since then, numerous studies have explored this risk-return tradeoff in attempts to estimate the magnitude of the tradeoff itself.

However, researchers have encountered two major difficulties in estimating the risk-return tradeoff for U.S. market portfolios. Some studies have found a positive relation between expected return and risk but others have even estimated negative risk-return tradeoffs (cf., Nelson, 1991 and Glosten, Jagannathan, and Runkle, 1993). More importantly, the estimated risk-return tradeoffs are not statistically significant in most studies. This has led researchers to investigate possible causes and solutions to this difficulty. For instance, Lundblad (2007) finds that a very long data span is required to discover a strong relation between expected return and risk. Anderson and Bollerslev (1998) and Bali and Peng (2006) show that high frequency data dramatically improve conditional volatility estimation. Despite these suggestions, a robust answer for the risk-return tradeoff is still being investigated.

In this paper, we investigate the nature of the risk-return tradeoff for the market portfolio and agribusiness assets (agricultural production and food manufacturing portfolio) using bivariate GARCH-M models. We also employ Bayesian inference to avoid a drawback of maximum likelihood estimation (MLE) which has usually been employed to estimate conditional volatility in GARCH specifications and take advantage of the existence of prior information. Lanne and Saikkonen (2006) report that high correlation between maximum likelihood estimates exists which leads statistical tests for a positive risk-return tradeoff

to have low power. Employing Bayesian estimation can help avoid this problem. Using the prior density, inequality constraints on the GARCH-M model volatilities are imposed properly in comparison with some previous studies.

We estimate high probabilities of positive risk aversion coefficients for the time-varying covariance and conditional volatility for agricultural production and the market portfolio. Since previous empirical results are very sensitive to variance specification, we also consider symmetric and asymmetric volatility specifications and, with two possible assumptions of the risk-return tradeoff, we find that Merton's theory is proper to explain the relation between return and risk.

Econometric Methodology

Theoretical model

The Merton(1973) ICAPM implies the following relation between risk and return:

$$r_i - r_f = \lambda_{im}\sigma_{im} \quad (1)$$

$$r_m - r_f = \lambda_m\sigma_m^2 \quad (2)$$

where r_i , r_m and r_f represent a return of a risky asset, the market portfolio and a risk free asset return, respectively, and σ_{im} and σ_m are the covariance between the return of the risky asset or portfolio i and the market portfolio m and conditional volatility of the market portfolio. λ_{im} in Eq. (1) and λ_m in Eq. (2) are the coefficients of relative risk aversion for a i th asset and the market portfolio, respectively, and both of them are expected to be positive.

Empirical framework

GARCH in mean models (GARCH-M: Engle, Lilien, and Robins, 1987; Bollerslev, Engle, and Wooldridge, 1988) have usually been employed to investigate the risk-return tradeoff. In this study, we use bivariate GARCH-M models and examine an i th asset or portfolio and the market portfolio jointly. GARCH-M consists of mean and variance equations. In this study, two different mean equations and sets of volatility specification are considered. The first set of mean equations we employ can be written as follows:

$$\begin{aligned} r_{i,t} - r_{f,t} &= \mu_i + \lambda_{im}h_{im,t} + \epsilon_{i,t} \\ r_{m,t} - r_{f,t} &= \mu_m + \lambda_m h_{m,t} + \epsilon_{m,t} \end{aligned} \quad (3)$$

where $h_{im,t}$ is the time-varying covariance between the returns of the market portfolio and the i th asset and $h_{m,t}$ is the conditional volatility of the return of market portfolio. The second set of mean equations used are:

$$\begin{aligned} r_{i,t} - r_{f,t} &= \mu_i + \lambda_i h_{i,t} + \lambda_{im} h_{im,t} + \epsilon_{i,t} \\ r_{m,t} - r_{f,t} &= \mu_m + \lambda_m h_{m,t} + \epsilon_{m,t} \end{aligned} \quad (4)$$

where $h_{i,t}$ is the conditional volatility of the return of i th risky asset.

The mean equation in Eq. (3) describes Merton's ICAPM, but in Eq. (4), we assume that an individual risky asset is explained by the time varying covariance with the market portfolio and its own conditional volatility.

Since the multivariate GARCH specification was introduced to model effects of time-varying conditional variances and covariances by Bollerslev, Engle, and Wooldridge (1988), many researchers have developed revised versions of multivariate GARCH model (for example, Engle and Kroner, 1995; Bollerslev, 1990; Engle, 2002).

In this study, we employ both symmetric (Bollerslev, Engle, and Wooldridge, 1988) and asymmetric VECH (Vector-GARCH) specifications (Kroner and Ng, 1998) to model the conditional variances and covariances. These specifications can be described as follows.

Symmetric VECH (Standard GARCH):

$$\begin{aligned} h_{i,t} &= \omega_i + \alpha_i \epsilon_{i,t-1}^2 + \beta_i h_{i,t-1} \\ h_{m,t} &= \omega_m + \alpha_m \epsilon_{m,t-1}^2 + \beta_m h_{m,t-1} \\ h_{im,t} &= \omega_{im} + \alpha_{im} \epsilon_{i,t-1} \epsilon_{m,t-1} + \beta_{im} h_{im,t-1} \end{aligned} \quad (5)$$

Asymmetric VECH (TARCH):

$$\begin{aligned} h_{i,t} &= \omega_i + \alpha_i \epsilon_{i,t-1}^2 + I \gamma_i \epsilon_{i,t-1}^2 + \beta_i h_{i,t-1} \\ h_{m,t} &= \omega_m + \alpha_m \epsilon_{m,t-1}^2 + M \gamma_m \epsilon_{m,t-1}^2 + \beta_m h_{m,t-1} \\ h_{im,t} &= \omega_{im} + \alpha_{im} \epsilon_{i,t-1} \epsilon_{m,t-1} + \gamma_{im} I \epsilon_{i,t-1} M \epsilon_{m,t-1} + \beta_{im} h_{im,t-1} \end{aligned} \quad (6)$$

where I and M are indicator functions for $\epsilon_{i,t-1}$ and $\epsilon_{m,t-1}$ respectively. If $\epsilon_{i,t-1}$ or $\epsilon_{m,t-1}$ is negative, the respective indicator function, I or M , equals one, and otherwise, they equal zero. The asymmetric VECH (TARCH) model is designed to allow negative errors to increase volatility more than positive errors. This phenomenon that negative errors

produce bigger risk than the same amount of positive one is usually called the “leverage effect.” The effect of negative errors is reflected in the parameter γ in each volatility specification and, as Campbell and Hentschel (1992) point out, the sign of γ is expected to be positive since a positive γ makes the conditional variance and covariance in next period increase.

We assume that the error term follows a normal density (see Campbell and Hentschel, 1993; Bali, 2008, for example) and the log-likelihood function is constructed by summing the log normal densities. The log-likelihood function (ignoring normalizing constants) for the bivariate model can be written as

$$L(r|\theta) = \sum_{t=1} L_t(r|\theta); \quad L_t(r|\theta) = -1/2 \cdot \log |\mathbf{H}_t| - 1/2 \varepsilon_t' \mathbf{H}_t^{-1} \varepsilon_t \quad (7)$$

where θ is a vector of the unknown parameters and ε_t and \mathbf{H}_t denote the error vector and time varying covariance matrix, respectively,

$$\varepsilon_t = \begin{bmatrix} \epsilon_{i,t} \\ \epsilon_{m,t} \end{bmatrix} \quad \text{and} \quad H_t = \begin{bmatrix} h_{i,t} & h_{im,t} \\ h_{mi,t} & h_{m,t} \end{bmatrix} \quad (8)$$

where $h_{im,t}$, the time-varying covariance, doesn't need to be positive but the covariance matrix, \mathbf{H}_t , has to be positive definite.

Bayesian Inference

In a Bayesian analysis of a statistical model there are two key components: the prior distribution and the likelihood function. The prior distribution describes the researcher's subjective prior beliefs concerning the relative probabilities of different possible values of model parameters; the likelihood function summarizes the information about those same relative probabilities of the values of model parameters conveyed in the data being analyzed. The posterior distribution results from the combination of the prior and the likelihood and is an optimal combination of those two information sources. Therefore, the posterior distribution summarizes all available information from the likelihood function and the prior information (Zellner, 1971).

The researchers' subjective beliefs are that 1) the conditional volatility over time needs to be positive without imposing any restrictions on the variance equation to keep all volatility estimates positive and 2) the conditional covariance can be negative but the time-varying covariance matrix must be positive definite over time. Using an indicator function, the positivity constraints are imposed on the conditional volatility directly instead of the parameters to keep the time-varying variance positive. This allows the parameters on

the variance equations to be negative because of the absence of inequality constraints and if negative parameters are more proper than positive ones, coefficients in variance equations (5) and (6) could be negative. This removes the chance of possible bias being introduced into the parameter estimates through unneeded nonnegativity constraints on the parameters in the (co)variance equations.

Another reason for being Bayesian is difficulties with maximum likelihood estimation (MLE). Lanne and Saikkonen (2006) point out that high correlation typically exists between ML estimators of the intercept, μ , and risk aversion coefficient, λ , in the mean equation on the univariate GARCH-M model. This creates a problem similar to multicollinearity in a normal regression model and leads to low power for statistical tests of whether λ is positive. Using Bayesian estimation, the difficulties of MLE can be avoided.

The prior densities for the individual parameters are set to independent normal densities with zero means and variance = 10^2 . This prior distribution is informative but due to the magnitude of prior variances, our prior distribution can be considered a diffuse prior. The prior distribution can be described as below:

$$p(\theta) = \mathbf{I}(\mathbf{H}_t) \cdot \prod_{i=1}^K N_{\theta_i}(0, 10^2) \quad (9)$$

where θ is the $(K \times 1)$ vector of parameters such as μ , λ , ω , α , and β and θ_i indicates the i th component of the parameter vector. The indicator function, $\mathbf{I}(\mathbf{H}_t)$, in the prior density equals one if the conditional variances for each time-series and covariance matrix in all time periods satisfy the conditions of positivity and zero otherwise.

Most of the information for the researcher's prior beliefs is created by the indicator function, $\mathbf{I}(\mathbf{H}_t)$. As Bauwens and Lubrano (1998) did, the initial variances $h_{i,0}$, $h_{m,0}$, and $h_{im,0}$ are treated as known constants. We can write our posterior distribution as

$$p(\theta|r) \propto p(r|\theta)p(\theta) \quad (10)$$

where $p(\theta|r)$ denotes the posterior density and $p(r|\theta)$ and $p(\theta)$ are the likelihood function and the prior distribution, respectively.

Previously, numerous studies have employed Bayesian inference to investigate the nature of GARCH processes (for example, Geweke, 1989; Kleibergen and van Dijk, 1993; Bauwens and Lubrano, 1998 and 2002; Nakatsuma, 2000; Vrontos, Dellaportas, and Politis, 2000; Osiewalski and Pipien, 2004; Lanne and Luoto, 2008). Since it is not feasible to compute the posterior analytically when the prior distribution is nonlinear or complicated, posterior simulators are employed in most of the studies. In this study, we employ the Random

Walk Chain Metropolis-Hastings algorithm because of its benefits in the absence of a good approximating density for the posterior distribution (Koop, 2003). In the Random Walk Chain Metropolis-Hastings algorithm, candidate draws are generated by a random walk process,

$$\theta^* = \theta^{(s-1)} + z, \quad (11)$$

where z is called the increment random variable. θ^* and $\theta^{(s-1)}$ are a candidate and previous draw from the posterior simulation, respectively. The coefficients of maximum likelihood estimation (MLE) are used as an initial value of candidate draws, $\theta^{(0)}$.

The choice of distribution for z , the increment random variable, determines the candidate generating density and the multivariate normal distribution is chosen in this study due to its convenience and our assumption of normality for the error term in Eq. (7). The candidate generating density can be described as follows:

$$q(\theta^*|\theta^{(s-1)}) = N(\theta^{(s-1)}, c \cdot \widehat{\Sigma}) \quad (12)$$

where $\widehat{\Sigma}$ is the covariance matrix from MLE and c is set to achieve an optimal acceptance rate.

The candidate draws are accepted or rejected with an acceptance probability that is computed as

$$\alpha(\theta^*|\theta^{(s-1)}) = \min \left[\frac{p(\theta = \theta^*|r)}{p(\theta = \theta^{(s-1)}|r)}, 1 \right] \quad (13)$$

where $p(\theta|r)$ is the posterior distribution. If the current draw is accepted, $\theta^{(s)}$ is θ^* . If rejected, the previous one is reused ($\theta^{(s)} = \theta^{(s-1)}$).

The acceptance rate of generated draws is critical for an accurate numerical approximation to the true distribution. However, there is no general rule for the optimal acceptance rate. Suppose that this rate is too high. In this case, the estimated posterior distribution will be very similar to the candidate generating density. On the other hand, too small an acceptance rate implies that the chain will not move enough to get information about the entire posterior density because candidate draws are almost always rejected and the region where the chain explores stays too close to the initial value. In both cases, it is highly doubtful that the posterior simulator investigates the entire posterior distribution well and the estimated posterior distribution is likely inaccurate. As Koop (2003) points out, the rule of thumb of the acceptance rate for candidate draws is around 0.5. If you achieve roughly 0.5 as the acceptance rate, the posterior simulation is likely to approximate

the posterior density correctly. To follow Koop’s suggestion, our acceptance rates for all estimations are calibrated to roughly 0.45 by choice of c in Eq. (12).

The posterior mean is commonly used as the point estimator of the posterior distribution. Since each accepted candidate draw is weighted equally in the Metropolis-Hastings algorithm, the simple average of all accepted candidate draws becomes the posterior mean. The posterior mean, \widehat{g}_S , can be written as

$$\widehat{g}_S = \frac{1}{S} \sum_{s=1}^S g(\theta^{(s)}). \quad (14)$$

where $g(\theta^{(s)})$ denotes any general function of the model parameters and S is the number of accepted draws.

We gather 55,000 accepted draws and discard the first 5,000 accepted draws as the initial burn-in to eliminate the effect of initial values. If a candidate draw does not satisfy the condition of positivity for the variance and covariance matrix, a draw is regenerated until it satisfies the researcher’s subjective belief (this is an accept-reject step within our posterior simulator to handle the truncation of the posterior distribution due to the indicator function in the prior for H_t).

For each estimation, we perform Geweke’s (1992) diagnostic to check the convergence of our Metropolis-Hastings algorithm. Let S_A and S_C denote first 10% and last 40% accepted draws. The test statistic for Geweke’s convergence diagnostic (CD) can be written as

$$CD = \frac{\widehat{g}_{S_A} - \widehat{g}_{S_C}}{\frac{\widehat{\sigma}_{S_A}}{\sqrt{S_A}} + \frac{\widehat{\sigma}_{S_C}}{\sqrt{S_C}}} \longrightarrow N(0, 1) \quad (15)$$

where \widehat{g}_{S_A} and \widehat{g}_{S_C} denote the posterior means of S_A and S_C , respectively. The terms $\frac{\widehat{\sigma}_{S_A}}{\sqrt{S_A}}$ and $\frac{\widehat{\sigma}_{S_C}}{\sqrt{S_C}}$ are the numerical standard errors of these two estimates.

In the MCMC algorithm, the posterior standard errors are different than the numerical standard errors (NSE) since the draws are correlated and a typical central limit theorem does not work. We compute the numerical standard errors using the formula suggested by Koop, Poirier, and Tobias (2007). The formula for the NSE is:

$$NSE(\widehat{g}_S) = \sqrt{\frac{\sigma^2}{m} \left[1 + 2 \sum_{j=1}^{m-1} \left(1 - \frac{j}{m} \right) \frac{\sigma_j}{\sigma^2} \right]} \quad (16)$$

where σ_j is the covariance between vectors $[\theta_1 \theta_2 \cdots \theta_{m-j}]$ and $[\theta_{j+1} \theta_{j+2} \cdots \theta_m]$ and σ^2 denotes the posterior variance of each parameter. Typically, $\sigma_j > 0$ and the numerical standard error is bigger than the posterior standard errors.

A posterior model probability is used to compare model specifications. A posterior model probability is computed by the product of marginal likelihood and prior model probability. Let M_i denote each of I different considered models for $i = 1, \dots, I$ and let $p(r|M_i)$ and $p(M_i)$ be the marginal likelihood of and a prior model probability of M_i , respectively. A posterior model probability can be described as

$$p(M_i|r) \propto p(r|M_i)p(M_i). \quad (17)$$

We set equal prior weights for all considered models, thus posterior model probabilities are proportional to the marginal likelihood values from the considered models. The marginal likelihood is computed to compare different models by simple averaging of all posterior densities of accepted draws. The model that has highest posterior model probability is considered the best specification.

Data Description

We use monthly return data on agricultural production and food manufacturing portfolios, the market portfolio, and the one-month Treasury bill rate as a risk free asset from the Kenneth R. French data library. The value-weighted CRSP index of NYSE, AMEX, and Nasdaq is employed for the U.S. total market returns and the return of agricultural production and food manufacturing portfolios. The two industries are part of the industry-specific returns from the 48 industry dataset. Agricultural production contains firms producing crops, livestock, commercial fishing, feeds for animals and agricultural services. Food manufacturing is industries such as food and kindred products, meat products, dairy products, etc. Exact details of the two industries are on the French data library webpage (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

Empirical results of bivariate GARCH-M models

Since this study is focused on the risk-return tradeoff for agribusiness portfolios and the market portfolio, we report only the results of parameters λ_i , λ_{im} and λ_m in the tables. For simplicity, we call the combination of Eq. (3) and Eq. (5) model (A) and the combination of Eq. (3) and Eq. (6) model (B). Models (C) and (D) will be the combination of Eq. (4) and Eq. (5) and the pairing of Eq. (4) and Eq. (6), respectively, in this section. Bayesian posterior simulation for each estimation satisfies Geweke's convergence diagnostic (test statistics available from the author).

Table 1 provides the empirical results of bivariate GARCH-M models between the market portfolio and agricultural production portfolio. For model (A), the coefficient for the time-varying covariance, λ_{im} , has greater than 95% posterior probability of being positive and the risk-return tradeoff for the market portfolio λ_m also has strong posterior support of being positive. For model (B), we also estimate positive λ_{ims} and λ_ms with high posterior probability.

In models (C) and (D), the risk aversion coefficient for the time-varying variance of the return on individual portfolio, λ_i , is added as a explanatory variable. The posterior distribution for λ_i in models (C) and (D), does not have strong posterior support of being positive or negative but the risk aversion coefficient for agricultural production and the market portfolio, λ_{im} and λ_m , both have over a 95% posterior probability of being positive. Based on the posterior model probabilities for four different frameworks, Merton's ICAPM employed in models (A) and (B) is heavily favored relative to the mean equation in models (C) and (D) and the GARCH specification in model (A) is slightly favored over the TARARCH specification in model (B).

In table 2, the empirical results for bivariate GARCH-M models between the market portfolio and food manufacturing portfolio are provided. Regardless of model specification, the risk aversion coefficients for conditional market volatility, λ_m , don't have as strong posterior support of being positive as with the agricultural production model. The risk aversion coefficients for time-varying covariance in models (A) and (B) don't have strong posterior support of being positive and surprisingly, strong posterior support for λ_{im} being negative is revealed in models (C) and (D). However, risk aversion coefficients for conditional volatility of food manufacturing portfolio, λ_i have greater than 95% posterior probability of being positive. The only similar pattern of the posterior GARCH-M results between agricultural production and food manufacturing portfolios is that model (A) has the largest posterior model probability. This supports that Merton's ICAPM is the favorite specification among the models we consider.

Figure 1 displays the conditional variances for agricultural production and the total U.S. market return and their time-varying covariance in model (A). The conditional volatility for agricultural production is much larger than that of the total U.S. market and the conditional covariance is similar in magnitude to the conditional volatility of the total U.S. market. Figure 2 shows the same series for the food manufacturing model in model (A). The conditional volatility of food manufacturing is smaller than that of the total U.S. market and the conditional covariance is also slightly smaller than the conditional volatility of the total U.S. market.

Conclusion

Since Merton's intertemporal capital asset pricing model was introduced, the relation between expected return and risk has been a centerpiece of modern finance. In this study, we investigate the risk-return tradeoff in the agricultural production and food manufacturing industry portfolios and the market portfolio using bivariate GARCH-M models.

With the agricultural production portfolio, we can estimate positive relations between stock return and its risk for the market portfolio with strong posterior supports but the posterior probability of a positive tradeoff for the market portfolio is lower with the food manufacturing industry. The agricultural production portfolio shows a positive risk-return tradeoff with high posterior probability but for the food manufacturing portfolio, a strong posterior support of a positive risk-return tradeoff is not revealed. Model (A) is favored over other models in both estimations. This implies that Merton's ICAPM and standard GARCH have strong posterior support.

The positive sign on the covariance between each industry and the total market, suggests that periods where agribusiness returns are more tightly correlated with the broader market are correctly perceived by the stock market as riskier periods for holding those assets.

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Table 1 Estimates of Bivariate GARCH-M Models for Agricultural Production

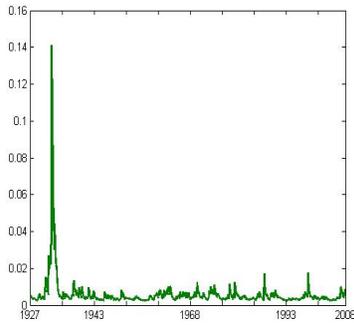
	Model (A)	Model (B)	Model (C)	Model (D)
λ_i			0.426	0.588
			(0.685)	(0.703)
λ_{im}	5.029	3.762	4.104	3.188
	(1.000)	(0.988)	(0.953)	(0.951)
λ_m	2.427	1.569	2.268	1.759
	(0.996)	(0.949)	(0.991)	(0.988)
Post. Model Prob.	0.564	0.406	0.015	0.015

Numbers in parentheses are a posterior probability of positive λ .

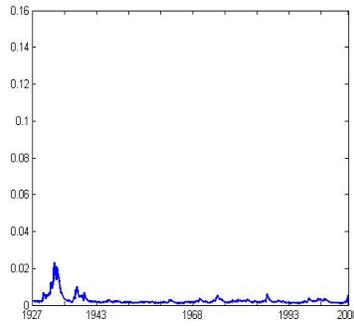
Table 2 Estimates of Bivariate GARCH-M Models for Food Manufacturing

	Model (A)	Model (B)	Model (C)	Model (D)
λ_i			4.186	4.141
			(0.991)	(0.992)
λ_{im}	1.160	0.983	-2.765	-3.054
	(0.906)	(0.864)	(0.041)	(0.046)
λ_m	0.917	0.776	0.524	0.204
	(0.879)	(0.829)	(0.745)	(0.609)
Post. Model Prob.	0.586	0.000	0.414	0.000

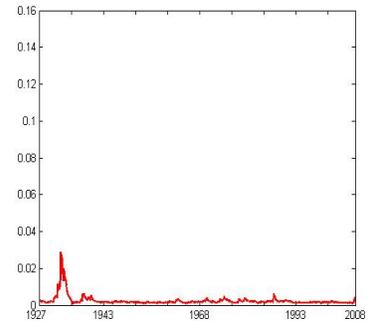
Numbers in parentheses are a posterior probability of positive λ .



Conditional Volatility
of Agriculture

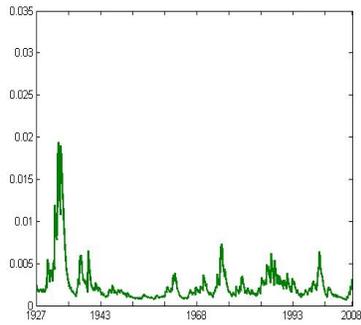


Conditional Volatility
of Total Market

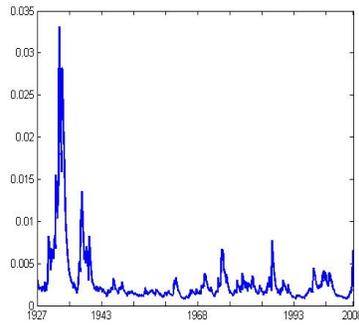


Conditional covariance
between Ag. and Market

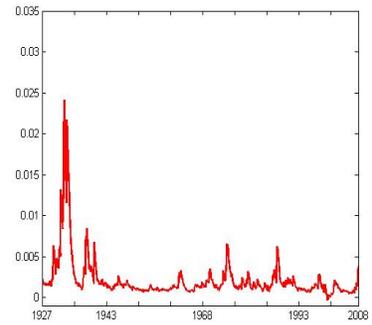
Figure 1 Conditional volatilities and covariance from the agricultural production bivariate model



Conditional Volatility
of Food



Conditional Volatility
of Total Market



Conditional covariance
between Food and Market

Figure 2 Conditional volatilities and covariance from the food manufacturing bivariate model