SAFEGUARDING FOOD SECURITY IN VOLATILE GLOBAL MARKETS

EDITED BY
ADAM PRAKASH

ISBN 978-92-5-106803-8

Cover design by Giancarlo de Pol
Cover photo (centre) ©FAO/Ami Vitale
Typesetting and layout by River Valley Technologies (river-valley.com)

Safeguarding food security in volatile global markets

Edited by Adam Prakash

Food and Agriculture Organization of the United Nations, Rome, 2011

Contents

Chapter 5

The nature and determinants of volatility in agricultural prices: an empirical study

Kelvin Balcombe[1]

The purpose of this chapter is to provide empirical support for the discussions in Chapters 3 and 4 that hypothesize determinants of price volatility, and to explore how the nature of volatility has evolved over the past few decades as demonstrated by the prices of 19 internationally-traded agricultural commodities.

In short, all of the price series are found to exhibit persistence in volatility (periods of relatively sustained high and low volatility). There is also strong evidence of transmission of volatilities across prices. Volatility in crude oil prices is found to be a significant determinant of volatilities in the majority of series and, likewise, the exchange rate volatility is found to be a volatility predictor in over half of the series. There is also strong evidence that stock levels and yields influence price volatility. Most series exhibit significant evidence of volatility trends. However, there is an upward direction for some series and a downward direction for others. Thus, there is no general finding of long-term volatility increases across all agricultural prices.

Background

Chapter 1 of this book empirically shows that the volatility in agricultural prices has changed over the recent decade, especially for three commodities key for food security: wheat, maize and soybeans. As discussed there, increasing volatility is a concern for agricultural producers as well as for other agents along the food chain. Price volatility can have a long-run impact on the incomes of many producers and the trading positions of countries, and can make planning production more difficult. Higher volatility results in an overall welfare loss (Aizeman & Pinto, 2005), though there may be some who benefit from higher volatility. Moreover, adequate mechanisms to reduce or manage risk to producers do not exist in many developing countries, and thus expose themselves to overall vulnerability. Therefore, an understanding the nature of volatility is required to mitigate its effects, particularly in developing countries, and further empirical work is needed to enhance our current understanding. In view of this need, this chapter seeks to study the volatility of a wide range of agricultural prices.

Importantly, the primary aim of studying volatility is not to trace the trajectory of the series itself or the determinants of its directional movements, but rather to describe the

1 School of Agriculture, Policy and Development, University of Reading, UK.

determinants of the absolute or squared changes in the agricultural prices.[2] I approach this problem from two directions: first, by directly measuring the volatility of the series and regressing it against a set of variables such as stocks, past volatility, etc.; and second, by modelling the behaviour of the series while examining whether the shock variances that drive price evolution can be explained by past volatility and other key variables.

More specifically, I employ two econometric methods to explore the nature and causes of volatility in agricultural price commodities over time. The first decomposes each of the price series into components and examines the volatility for each. Using this approach I examine whether volatility in each price series is predictable, and whether it is dependent on: stocks; yields; export concentration; the volatility of other prices including oil prices, exchange rates and interest rates. This first approach will be used to analyse monthly prices.[3] The second uses a panel regression approach whereby volatility is explained by a number of key variables. This approach has a drawback, however, as several of these key variables - notably inventories and yields - are only observed at the annual frequency, limiting the sample size and masking the intra-year variability of the series.

On a methodological level, our strategy differs from previous work in this area by its treatment of the variation in volatility of both trends and cyclical components (should a series contain both) of the series. Previous work has tended to focus on either one or the other. Alternatively, studies that have used a decomposed approach have not employed the same decomposition as is done here. Importantly, in contrast to many other approaches, the framework I use to analyse monthly data requires no prior decision about whether the series contains trends.

Modelling volatility processes

While the volatility of a time series may seem like a rather obvious concept, there are in fact several different potential measures of a series' volatility. For example, if a price series has a mean,[4] then the volatility may be interpreted as its tendency to have values very far from this mean. Alternatively, volatility may be interpreted as a series' tendency for large changes in its values from period to period. A high rate of volatility according to the first measure need not imply a high volatility according to the second. Another commonly held notion is that volatility is defined in terms of the degree of forecast error. A series may have large period-to-period changes, or large variations away from its mean, but if the conditional mean of the series is able to explain most of the variance, then a series may not be considered volatile.[5] Thus, a universal measure of what seems to be a simple concept is in fact quite elusive. Where series contain trends, an appropriate measure of volatility can be even harder to define. This is because the mean and variance (and other moments) of the data-generating process do not technically exist. Methods that rely on sample measures can therefore be misleading.

Shifts in volatility can come in at least two forms: First, an overall permanent change (whether a gradual shift or a break) in the volatility of the series; and, second in a "periodic" or "conditional" form whereby the series appears to have periods of relative calm and others

2 In order to model volatility, it may be necessary to model the trajectory of the series. However, this is a necessary step rather than an aim in itself.

3 Data of varying frequencies are used not for theoretical reasons, but owing to availability. The data were provided by FAO.

4 That is, the underlying data-generating process has a mean, not just the data, in the sample.

5 This definition is embodied in the notion of "implied volatility", whereby futures or options prices relative to spot prices are used to measure volatility.

of high volatility. The existence of the periodic form of volatility is now empirically well-established for many economic series. Speculative behaviour is sometimes seen as a primary source of changeable volatility in financial series. The vast majority of the evidence for periodic changes in volatility is in markets where there is a high degree of speculation. This behaviour is particularly evident in stocks, bonds, options and futures prices. For example, booms and crashes in stock markets are almost certainly exacerbated by temporary increases in volatility.

While there is less empirical evidence about volatility changes in agricultural commodity markets, there is nonetheless some strong empirical evidence that this is the case. Moreover, there are good *a priori* reasons to think that changes in volatility might exist. For example, Deaton and Laroque's models (Deaton & Laroque, 1992) based on the theories of competitive storage suggest, *inter alia*, that variations in price volatility should exist. Moreover, market traders to some extent act in a similar way to the agents that determine financial series. They are required to buy and sell according to fluctuating conditions and there is money to be made by buying and selling at the right time. However, agricultural commodity prices are different from most financial series owing to the fact that both their of production and stock levels are likely to be an important factor in determining their prices (and the volatility of these prices) at a given time. The connectedness of agricultural markets to other markets experiencing volatility variation (such as energy) may also influence the volatility of agricultural commodities.

For a series with a stable mean value over time (mean reverting[6]), the variance of that series would seem to be an obvious statistic to describes its *ex ante* (forward looking) volatility.[7] More generally, if a series can be decomposed into components such as trend and cycle, the variance of each can describe the volatility of the series. The use of the term *ex ante* requires emphasis, because clearly a price series can have relatively large or small deviations from its mean without implying a shift in its overall variability. It is important to distinguish *ex ante* from *ex post* (historical or backward looking) volatility. One might believe that comparatively high levels of historical volatility are likely to lead to higher future volatility, but this need not be the case.[8] However, the variance of the series (or component of the series) may be systematic and predictable given its past behaviour. Thus, there will be a link between changes in *ex ante* and *ex post* volatility. Where such a link exists, the series is more likely to behave in a way where there are periods of substantial instability. It is for this reason that primary interest is in changes in *ex ante* volatility, and whether it can be predicted using historical data.

A wide range of models dealing with systematic volatility have been developed since the seminal work proposed by Engle (1982).[9] The vast majority of volatility work continues to focus on series where the future trajectory cannot be predicted from its past. Financial and stock prices behave in this way. Simply focusing on the variability of the differenced series is sufficient in this case. However, this may not be appropriate for many other series (such as agricultural prices), as there is evidence that they are cyclical, and either contain or do

6 A mean reverting series obviously implies that an unconditional mean for the series exists, and that the series has a tendency to return to this mean. This is less strong than assuming a condition called stationarity, which would assume that the other moments of the series are also constant (see Chapter 2).

7 If the series has a distribution with "fat tails", even the variance may give an inaccurate picture of the overall volatility of a series.

8 For this reason, some writers make the distinction between the realized and the implied volatility of a series.

9 For a number of papers on this topic, see Engle (1995) and the survey in Oxley et al. (1994).

not contain trends that require modelling within a flexible and unified framework. Deaton & Laroque (1992), citing earlier papers, note that many commodity prices also behave in a manner similar to stock prices (the so-called "random walk" model). However, they also present evidence that is inconsistent with this hypothesis. They note that within the random walk model, all shocks are permanent, and that this is implausible with regard to agricultural commodities (i.e. weather shocks would generally be considered transitory). In view of the mixed evidence about the behaviour of agricultural prices, I stress the importance of adopting a framework that can allow the series to have either trends or cycles or a combination of both. Importantly, there may be alterations in the variances that drive both of these components. Therefore, for the purposes of this chapter, I adopt the approach that allows for change in volatilities of both components should they occur, but does not require that both components exist.

From the point of view of this study, it is not just volatility in the forecast error that is important. Even if food producers were able to accurately forecast prices a week, month or even year in advance, they may still be unable to adapt accordingly. Aligned with this point, it may be unrealistic to believe that agricultural producers would have access to such forecasts, even if accurate forecasts could be made. Thus, I take the view that volatility can be a problem even if large-scale changes were anticipated given past information. This viewpoint underpins the definitions of volatility employed in this study.

Our definitions of volatility are also influenced by the frequencies of the available data. Because the price data for the majority of series are monthly (with a number of explanatory variables at the annual frequency), I created a measure of annual volatility using the monthly price data. "Annual volatility" should not be defined just by the difference between the price at the beginning and end of the year. Any measure should take account of the variability within the year. Therefore, to create the annual volatility measures I take yearly volatility as the log of the square root of the sum of the squared percentage changes in the monthly series. Admittedly, this is one possible measure among many. However, it is a convenient summary statistic that is distributed approximately normal, and is therefore usable within a panel regression framework. This statistic is an *ex post* measure of volatility. Year to year changes in this statistic do not imply that there is a change in the underlying variance of the shocks that are driving this series. However, any shift in the variability of the shocks that drive prices is likely to be reflected in this measure.

When focusing on the higher frequency data, this study defines volatility as a function of the variance of the random shocks that drive the series along with its serial correlation. This volatility is then decomposed into "cyclical" and "level" components. Within this approach, volatility is not just defined in terms of *ex post* changes in the series, but in terms of the underlying variance of the shocks governing its volatility. The influence of other variables on these variances can be estimated using this method. Our approach (the decomposition approach) is outlined at a general level in the following section.

Before proceeding, it is worth noting some other aspects of commodity price behaviour that are not directly explored in this chapter. Other "stylized facts" of commodity price distributions may be "skew" and "kurtosis". Skew suggests that prices can reach occasional high levels that are not symmetrically matched by corresponding lows, and that prices spend longer in the "doldrums" than at higher levels (Deaton & Laroque, 1992). Kurtosis suggests that extreme values can occur occasionally. Establishing measurements of skew and kurtosis of price distributions can be extremely difficult when the prices contain cycles and/or trends and have time-varying volatility. Some of the previous empirical work that supports the existence of skew and kurtosis has been extremely restrictive in the way the series was modelled (e.g. they assumed that the series are mean reverting). Moreover, kurtosis in unconditional price distributions can be the by-product of conditional volatility, and by conditioning the volatility of prices on the levels of stocks one may be able to account for the apparent skew in the distributions of prices. Thus, some of the other "stylized facts" may in reality be a by-product of systematic variations in volatility.

Potential factors influencing volatility

It has been argued that agricultural commodity prices are volatile because the short-run supply (and perhaps demand) elasticities are low (Dehn et al., 2005). If this is indeed a major reason for volatility, then one should see a change in the degree of volatility as production and consumption conditions evolve.

Regardless of the definition of volatility, there is ample empirical evidence that the volatility of many time series do not stay constant. For financial series, the literature is vast. For agricultural prices the literature is smaller. However, changes in volatility are evident in simple plots of the absolute changes in prices from period to period. These changes demonstrate that there is a shift in the average volatility of many agricultural prices, a fact further supported by evidence on implied volatility (FAO, 2008). This occurs against the backdrop of the general move towards market liberalization and global markets, along with dramatic changes in the energy sector with its increasing production of biofuels. I consider various factors listed below, each with a short justification. Owing to data constraints, it is not possible to include all factors in the same models over the whole period. Therefore, a subset of these factors enters each of the models depending the frequency of the data used in estimation.

Past volatility: the principles underlying Autoregressive Conditional Heteroscedasticity (ARCH) and its generalized forms (e.g. GARCH) posit that while there are periods of relatively high and low volatility, the underlying unconditional volatility remains unchanged. Evidence of ARCH and GARCH is widespread in series that are partly driven by speculative forces and may also be present in the behaviour of agricultural prices.

Trends: there may be long-run increases or decreases in the volatility of the series. Our study accounts for them by including a time trend in the variables that explain volatility. While an alternative is that volatility has a stochastic trend (i.e. a trend that cannot be described by a deterministic function of time), this possibility is not investigated here.

Stock levels: as commodity stocks fall, it is expected that price volatility will increase. If stocks are low, then the dependence on current production in order to meet short-term consumption demands is likely to rise. Any further shocks to yields could therefore have a more dramatic effect on prices. As noted earlier, the storage models of Deaton & Laroque (1992) have played an important role in theories of commodity price distributions. Their theory explicitly suggests that time-varying volatility will result from variations in stocks.

Yields: obviously, the yield for a given crop can drive the price for a given commodity either up or down. A particularly large yield (relative to expectations) may drive prices down, and a particularly low yield may drive them up. However, in this chapter the concern is not with the direction of change, but rather with impact on the absolute magnitude of the changes. If prices respond symmetrically to yields then one might expect no impact on the volatility of the series. However, if a large yield has a greater impact on prices than a low yield, then it might be expected that volatilities are positively related to yields. Conversely, if a low yield has a greater impact on prices than a high yield, then volatilities are negatively related to yields. It is difficult to say a priori which direction yields are likely to push volatility, if they influence the level of volatility at all. For example, a high yield may have dramatic downward pressure on price (downwards, increasing volatility). However, this higher yield may also lead to larger stocks in the following year (decreasing volatility in a subsequent period).

Transmission across prices: a positive transmission of price volatility is expected across commodities. International markets experience global shocks that are likely to influence global demand for agricultural prices, and these markets may also adjust to movements in policy (trade agreements, etc.) that may impact a number of commodities simultaneously. Additionally, volatility in one market may directly impact on the volatility of another where stocks are being held speculatively.

Exchange rate volatility: the prices that producers receive once they are deflated into the currency of domestic producers may have great impact on the prices at which they are prepared to sell. This also extends to holders of stocks. Volatile exchange rates increase the riskiness of returns, and thus it is expected that there may be a positive transmission of exchange-rate volatility to the volatility of agricultural prices.

Oil price volatility: perhaps one of the biggest shifts in agricultural production in the past few years, and one that is likely to continue, is the move towards biofuels. Empirical work has suggested a transmission between crude oil and sugar prices (Balcombe & Rapsomanikis, 2008). It is also likely that there is a strong link between input costs and output prices. Fertilizer prices, mechanized agriculture and freight costs are all dependent on oil prices, and will feed through into the prices of agricultural commodities. In view of the fact that the price of oil has shown unprecedented realized volatility over the past few years, there is clearly the potential for this volatility to spill over into commodity prices.

Export concentration: fewer exporting countries could expose international markets to variability in their exportable supplies. This variability might stem from weather shocks and domestic events such as policy changes. Lower Herfindahl concentration (the index I use here) would lead to higher potential volatility and vice versa.

Interest rate volatility: interest rates are an important macroeconomic factor that can have a direct effect on the price of commodities because they represent a cost to stock holding. However, they are also an important indicator of economic conditions. Interest rate volatility may therefore indicate uncertain economic conditions and subsequent demand for commodities.

Models employed

This section will outline at a general level the main elements of the models used for our analysis. As discussed in the preceding sections, I use two main methods. Each is dealt with below.

Random parameter models with time varying volatility

At the heart of this approach is the decomposition for the logged price y_t at time t :

$$y_t = Level_t + Seasonal_t + Cycle_t \tag{1}$$

The level component may either represent the mean of the series (if it is mean reverting) or may trend upwards or downwards. The cyclical component, by definition, has a mean of zero and no trend. However, the level components are driven by a set of shocks (v_t), and the cyclical components are driven by shocks (e_t). Each of these is assumed to be random, governed by a time varying variances h_{vt} and h_{et} respectively. Either of these variances may be zero for a given price, but both cannot be zero as this would imply that the series has no random variation. For the level component, a variance of zero would imply a constant mean for the series, and therefore that all shocks are transitory. If the cyclical variance was zero, this would imply that all shocks to prices were permanent.

The seasonal component is deterministic (does not depend on random shocks). I explored two different methods of modelling seasonality. The first used "seasonal dummies", whereby the series is allowed a seasonal component in each month. The second was Harvey's (Harvey, 1989, p. 41) seasonal frequency approach. Here, there are potentially 11 seasonal frequencies that can enter the model, the first of which is the "fundamental frequency". The results were largely invariant to the methods employed. However, our results presented in the empirical section use the first seasonal frequency method only. The level and cyclical components have variance, which is labelled as follows:

$$Var(\Delta Level_t): \ volatility\ in\ mean \tag{2}$$
$$Var(Cycle): \ volatility\ in\ cycle \tag{3}$$

Each of these is governed by an underlying volatility of a shock specific to each component and is shown to be:

$$Var(\Delta Level_t) = Constant_L \times h_{v,t} \tag{4}$$
$$Var(Cycle_t) = Constant_C \times h_{e,t} \tag{5}$$

Formally, for a given price series y_t (or logged series which will be used throughout this chapter) where $t = 1.....T$, it is proposed that the following autoregressive model with a random walk intercept is used:

$$\theta(L) y_t = \alpha_t + \delta' d_t + e_t \tag{6}$$

where $\theta L = \sum_{i=0}^{k} \{\theta_i L^i\}$ (a lag operator of finite length) and:

$$\alpha_t = \alpha_{t-1} + v_t \tag{7}$$

where d_t is a vector of deterministic variables[10] that are able to capture the seasonality and e_t and v_t are assumed to be independently normally distributed. The series can then be decomposed into its components:

$$Level: \ \mu_t = \theta(L)^{-1}(1-L)^{-1} v_t \tag{8}$$
$$Seasonal: \ s_t = \delta' \theta(L)^{-1} d_t \tag{9}$$
$$Cycle: \ (y_t - a_t - s_t) = \theta(L)^{-1} e_t \tag{10}$$

This therefore allows the separate analysis of the non-stationary component and the stationary component $(y_t - \mu_t)$. The overall volatility of the series is governed by the two variances $h = (h_v, h_e)$ along with the autoregressive parameters. The observed volatility is produced by the errors e_t, v_t (which are assumed to be iid normal). The inverted lag operator has the representation:

$$\theta(L)^{-1} = \sum_{i=0}^{\infty} \gamma_i L^i \tag{11}$$

[10] In this case I examined both standard seasonal dummies along with the seasonal effects variables in Harvey (1989, p. 41). In virtually variables I found little evidence of seasonality. For the results presented in this report, I continue to include the first fundamental frequency. However, in nearly all cases this was not significant. I continue to include it for consistency across models. However, removing the seasonal dummies would make little difference to the results presented here.

In the absence of stochastic volatility, the volatility in each of the series is governed by:

$$Var(\Delta\mu_t) = \left(\sum_{j=0}^{\infty}\gamma_j^2\right)h_v \tag{12}$$

$$Var(y_t - \mu_t) = \left(\sum_{j=0}^{\infty}\gamma_j^2\right)h_e \tag{13}$$

For a stationary series $h_v = 0$, in which case only $Var(y_t - \mu)$is of interest. The proposed framework is able to cope with stationary or non-stationary series, as there is no requirement that h_v> 0 within the model. For the purposes of this study, the distinction between two volatilities will be made as follows:

$$Var(\Delta\mu_t): \ volatility\ in\ mean \tag{14}$$

$$Var(y_t - a_t - s_t): \ volatility\ in\ cycle \tag{15}$$

The model can be extended by conditioning the variances on a set of explanatory variables in the following way:

$$\ln h_{v,t} = ln(h_v) + \lambda_v' z_t \tag{16}$$

$$\ln h_{e,t} = ln(h_e) + \lambda_e' z_t \tag{17}$$

where z_t is a vector of variables determining volatility. The two measures of volatility at a particular time then become:

$$Var(\Delta\mu_t) = \left(\sum_{j=0}^{\infty}\gamma_j^2\right)h_{v,t} \tag{18}$$

$$Var(y_{\{t\}} - \mu_t) = \left(\sum_{j=0}^{\infty}\gamma_j^2\right)h_{e,t} \tag{19}$$

(where these can be aggregated to overall measure of volatility).

Restrictions and identification

In the framework outlined above, (16) and (17) imply that the underlying volatility is governed by:

$$h_{v,t} = h_v \exp(\lambda_v' z_t) \tag{20}$$

$$h_{e,t} = h_v \exp(\lambda_e' z_t) \tag{21}$$

If λ_v or λ_e are equal to zero then the volatility in the long- or short-run component are constants. However, in the situation where h_v or h_e are zero, then the associated parameters $\lambda\ or\ \lambda_e$ become unidentified. This does not in itself preclude estimation within in a Bayesian framework. However, unless the posterior densities of h_v and h_e are both heavily concentrated away from zero, then the standard error of the lambda coefficients will be very large. If a series can be modelled in a way that the variance could be attributed either to stationary or non-stationary shocks, then the associated standard deviation in the estimates of the lambda coefficients will be large, and determining whether the shocks in the variable in question are significant will be very difficult. I avoid this problem in this study by assuming $\lambda_v = \lambda_e = \lambda$. This implies that the long- and short-run variances are proportional, but that they can vary across in t. As the values of h_v and h_e will not be close to zero simultaneously (as all the series have variation) the standard errors in the lambda coefficients will be smaller. This obviously comes at a cost. If the shocks to volatility (z_t) impact the long- and short-run components differently, then clearly there would be bias in the results. However, arguably, it is reasonable to assume that shocks in volatility are likely to co-vary across both the permanent and transitory components (should they both exist). Thus, while this assumption is essentially required for identification, it is highly plausible from an economic point of view.

Estimation

Denoting the parameters that are to be estimated as Ω, the data to be explained as Y and the explanatory data as X, the likelihood function can be viewed as the probability density of Y conditional on X andΩ. Therefore, the likelihood function can be denoted as$f(Y|\Omega,X)$. For prior distributions on Ω, $f(\Omega)$, the posterior distribution is denoted as $f(\Omega|Y,X)$ and obeys:

$$f(\Omega|Y,X) \propto f(Y|\Omega,X)\,f(\Omega) \tag{22}$$

where$\propto$denotes proportionality. For the random parameter models, the parameters of interest are:

$$\Omega_* = \left(\left\{\theta_j\right\}, \lambda_v,\ \lambda_e,\ h_v,\ h_e\right) \tag{23}$$

Normal priors are adopted for the parameters $\left\{\theta_j\right\}, \lambda_v, \lambda_e$ where the mean is zero, with a large variance so as to reflect diffuse prior knowledge.[11] For the parameters h_v and h_e inverse gamma priors can be used, as is standard in Bayesian analysis.

For any values of $(\lambda_v, \lambda_e, h_v, h_e)$ the Kalman Filter can produce optimal estimates of $\left\{\theta_j\right\}$ and standard errors for these parameters, along with the value of the likelihood function. Thus, in effect $\left\{\theta_j\right\}$ are ignored in the estimation of Ω as they are viewed as latent variables that are generated for any given values of Ω but are not required for the likelihood function. Estimations of the posterior distributions are then obtained using a random walk Metropolis-Hastings algorithm (see Koop, 2003, p. 97) to simulate the posterior distribution. The estimates of $\Omega(\overline{\Omega})$ that are then produced are the mean of the simulated parameters and the standard deviations for the simulated values can likewise be obtained. The estimates for $\left\{\theta_j\right\}$ along with the standard errors are then obtained using the values $\overline{\Omega}$ within the Kalman Filter.[12]

One can also look to the Bayesian approach to estimate panel data, in this case using Gibbs Sampling.[13] The parameters are simply:

$$\Omega = (\{\beta_{oi}\}, \{\beta_{1i}\}, \lambda_v, \lambda, \Sigma) \tag{24}$$

where Σ is the variance covariance matrix associated with the errors in equation (4).

Having made this decomposition, then one can make h_{vt} and h_{et} depend on explanatory variables. Within this chapter I consider the following explanatory variables for driving volatilities, which I have discussed earlier:

11 Note that the priors for the autoregressive coefficients are set within the Kalman Filter.

12 Note that these point estimates are therefore conditional on the plugin estimates and strictly speaking do not reflect the mean and variance of these parameters from a Bayesian perspective.

13 Good coverage of Gibbs Sampling is provided in many textbooks. The estimation procedure of this panel can be viewed as a seemingly unrelated regression with cross equation restrictions. The details of how to estimate this model are in Koop (2003, chapter 6).

1. A measure of the past realized volatility of the series ;
2. Realized oil price volatility;
3. A measure of the average realized volatility in other agricultural prices within the data;
4. Stock levels;
5. Realized exchange rate volatility;
6. Realized interest rate volatility; and,
7. A time trend.

In each case where I use the term "realized" volatility, the measure is the square of the monthly change in the relevant series, as distinct from the *ex ante* measures h_{vt} and h_{et}respectively. Using the approach above, I then produce:

1. Measures in volatility (mean and cycle) for each of the agricultural price series through time;
2. Tests for the persistence in the changes in volatility for these series;
3. Tests for the transmission of volatility across price series; and;
4. Tests for the transmission of volatility from oil prices, stocks etc. to agricultural prices.

The panel approach

In order to complement the approach described above, I also used annual data in our analysis. A panel approach is most appropriate for needs owing to the relatively short series available (overlapping across all the variables) at the annual frequency. I employed the following approach:[14]

$$\ln V_{it} = \beta_{0i} + \beta_{1i}t + \lambda_v \ln V_{i(t-1)} + \lambda z_{it} + e_{it} \tag{25}$$

where V_{it} is a (realized) measure of volatility of the ith commodity at time t, z_{it} is a vector of factors that could explain volatility, and e_{it} is assumed to be normal with a variance that is potentially different across the commodities, serially independent, but with a covariance across i (commodities). I additionally estimate the model imposing $\beta_{1i} = \beta_1$ (a common time trend) across the models. Thus this model is one with fixed effects (intercept and trend) across the commodities.[15] Within z_{it} I consider the following:

1. Realized oil price volatility;
2. Stocks;
3. Yields;
4. Realized exchange rate volatility; and,
5. Realized export concentration (the Herfindahl index).

Where the price data are monthly, the realized annual volatility is defined herein as:

$$V_{it} = \sqrt{\frac{\sum_{j=1}^{12} \left(\Delta ln\left(p_{i.j.t}\right)\right)^2}{12}} \tag{26}$$

[14] The distribution of the volatilities was examined prior to estimation, and showed that the logged volatilities had a distribution that was reasonably consistent with normal. Therefore, estimation was conducted in logged form.

[15] The issues of trends, stochastic trends and panel cointegration are not considered in this report. The volatilities are unlikely to be I(1) processes, and certainly reject the hypothesis that they contain unit roots. Stochastic trends could exist in the stocks, yield and export concentration data, and I recognize therefore these could have an influence on the results.

where $p_{i.j.t}$ is the price of the ith commodity in the j^{th} month of the t^{th} year. As noted earlier, there are a number of other potential measures of annual volatility. However, the statistic above usefully summarizes intra-year volatility into an annual measure. Alternative transformations (such as the mean absolute deviation of price changes) are very similar when plotted against each other, and are therefore likely to provide similar results within a regression framework. The logged measure of volatility, as defined in (26), is approximately normally distributed for the annual series used in the analysis, which is attractive from an estimation point of view.

Estimation and interpretation

This study employs a Bayesian approach to estimation, which is viewed as a more robust method in the current context. The estimation of the random parameter models can be performed using the Kalman Filter (Harvey, 2007). The Kalman Filter enables the likelihood of the models to be computed, and may be embedded within Monte Carlo Markov Chain (MCMC) sampler that estimates the distributions of the parameters of interest.[16]

Interpreting parameter estimates and standard deviations

In interpreting the estimates, readers may adopt an essentially classical approach (i.e. the statistical approach with which most readers are likely to be familiar). Strictly speaking, the Bayesian method requires some subtle differences in thinking. However, there are theoretical results (see Train, 2003) establishing that using the mean of the posterior (the Bayesian estimate of a parameter) is equivalent to the "maximum likelihood" estimate (one of the most commonly used classical estimates) which shares the property of asymptotic efficiency. As the sample size increases and the posterior distribution normalizes, the Bayesian estimate is asymptotically equivalent to the maximum likelihood estimator and the variance of the posterior identical to the sampling variance of the maximum likelihood estimator (Train, 2003). Therefore, I will continue to talk in terms of "significance" of parameters, even though strictly speaking p-values are not delivered within the Bayesian methodology (and for this reason are not produced within our results section). More broadly, if the estimate is twice as large as its standard deviation, then this is roughly consistent with it being statistically significant at the 5 percent level.

Data and empirical results

The data for this study were provided by the FAO. A summary of the length and frequency of the data is provided in Table 5.1. The models discussed in the previous section will be estimated using these data. The first set of models outlined in time-varying approach will be run on the monthly series, and the panel approach will be used for the annual data. The annual price volatilities were calculated from the monthly data. There are 19 commodities listed in the tables.

Because some of the variables were recorded over a shorter period than others, the models will be run using a subset of the data. Where stocks are used at a monthly frequency,

[16] A full description of the estimation procedures is beyond the scope of this chapter; even though many of the methods are now standard within Bayesian econometrics, a full description would run many pages. Good starting references include Chib & Greenberg (1995) and Koop (2003).

they were interpolated from the quarterly data, but the models were estimated at the shorter frequency.[17]

Monthly results

I begin with the results for the monthly data run over the longest possible period for each commodity. In the first instance exchange rates were not included, as these were available only from 1973 onwards (see Table 5.1). The models using monthly data were then re-estimated including exchange rates (over the shorter period). When running the models, I imposed positivity restrictions on the coefficients of some of the explanatory variables. Without these restrictions, a minority of commodities had perverse signs on some of the coefficients, though in nearly all cases these were insignificant. The monthly results are presented in Tables 5.2. In each case the results for the model with and without exchange rates are presented for each commodity. Importantly, the time period over which the two sets of results are obtained differs for the case where exchange rates are included, as exchange rates were only available from 1973 onwards. The difference in the parameter values will therefore differ owing to this as well as to the inclusion of exchange rates. Table 5.3 presents the monthly results for the three series for which stocks data are available.

In Table 5.2 through 5.5, the error variance refers to the square root estimate of the intercept for h_e as defined previously. The Random intercept variance is the square root of the intercept estimate of h_v. The rest of the parameter estimates are the λ parameters in equations (16) and (17) where these are the coefficients of the variables listed in the first column of each table. The last four coefficients in each table include: the intercept; estimates of the autoregressive coefficients; and the seasonal coefficient (the first fundamental frequency).

The estimates within the table are the means and standard deviations of the posterior distributions of the parameters. In each case the significance of a variable is signified by the estimate in bold italics indicating that the standard deviation is less than 1.64 of the absolute mean of the posterior distribution. As noted earlier, this roughly corresponds to a variable being significant at the 5 percent level (one-tailed).

While the focus of our analysis is mainly on the determinants of series volatility, it is worth noting that the autoregressive representation of order two is sufficient to capture the serial correlation in the series. The first lag is significant for most of the commodities. In only a few cases is the second-order coefficient significant. Having said this, however, the majority of the series have negative second-order coefficients suggesting that most of the series contain cyclical behaviour. The seasonal components of the series are insignificant for nearly all commodities.[18] While the second-order coefficient and seasonal components could be removed, an exploratory analysis suggests that inclusion of these components had no substantive impact on the results. Therefore, for consistency, these explanatory variables are included for all the series.

Table 5.5 summarizes the results for the monthly data from Tables 5.2 through 5.3. Each series has two sets of results. The first is where the model is run on the longest possible period, excluding exchange rate volatility. The second is on the shorter series where exchange rate volatility is included. Therefore, the two sets of results will differ because an additional

[17] Weekly prices also exist for a few commodities only. Data were analysed, but the results were rather inconclusive. Our analysis of these data is not included in this chapter but can be made available.

[18] This finding was supported when the series were estimated with higher seasonal frequencies and seasonal dummies.

variable is included and they are run over different periods. The stocks data were available for only three of the series (wheat, maize and soybean). Therefore, I provide another table (Table 5.3) which utilizes the stocks data. Again, this is run over a shorter period than for all the previous results, as the stocks data are only available from the periods listed in Table 5.1. The rest of the column in Table 5.1 is blacked out for the other commodities for which stocks data are unavailable. A tick (√) in a given cell indicates that the variable listed in the column heading is significant in influencing the volatility of the series for one of the models in

Table 5.1: Data series summary for modelling price volatility

	Frequency series	Annual stocks	Annual yield	Annual herfindel	Monthly price	Quarterly stocks
Commodity						
Wheat	1	1962-2007	1962-2007	1961-2006	Jan 1957-Mar 2009	Jun 1977-Dec 2008
Maize	2	1962-2007	1962-2007	1961-2006	Jan 1957-Mar 2009	Jun 1975-Jun 2008
Rice, milled	3	1962-2007	1962-2007	1961-2006	Jan 1957-Mar 2009	
Oilseed, soybean	4	1962-2007	1962-2007	1961-2006	Jan 1957-Jan 2009	Dec 1990-Dec 2008
Oil, soybean	5	1962-2007		1961-2006	Jan 1957-Jan 2009	
Oil, rapeseed	6	1962-2007	1962-2007	1961-2006	Jan 1970-Jan 2009	
Oil, palm	7	1962-2007	1962-2007	1961-2006	Jan 1960-Jan 2009	
Poultry, meat, broiler	8	1962-2007		1961-2006	Feb 1980-Nov 2008	
Meat, swine	9	1962-2007		1961-2006	Feb 1980-Nov 2008	
Meat, beef and veal	10	1962-2007		1961-2006	Jan 1957-Oct 2008	
Dairy, butter	11	1962-2007		1961-2006	Jan 1957-Jan 2009	
Dairy, milk, non-fat dry	12	1962-2007		1961-2006	Jan 1990-Jan 2009	
Dairy, dry whole milk powder	13	1962-2007		1961-2006	Jan 1990-Jan 2009	
Dairy, cheese	14	1962-2007		1961-2006	Jan 1990-Jan 2009	
Cocoa	15		1962-2007	1961-2006	Jan 1957-Nov 2008	
Coffee, green	16	1962-2007	1962-2007	1961-2006	Jan 1957-Nov 2008	
Tea	17		1962-2007	1961-2006	Jan 1957-Nov 2008	
Sugar	18	1962-2007	1962-2007	1961-2006	Jan 1957-Nov 2008	
Cotton	19	1962-2007	1962-2007	1961-2006	Jan 1957-Nov 2008	
Other data						
Oil prices					Jan 1957-Mar 2009	
Exchange rates					1973-2007	
Interest rates (US 6 month treasury bill)						

Table 5.2: Random parameter models: results (without stocks)

(a) Wheat (monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error variance	*0.02*	0.007	*0.029*	0.01
Random intercept	*0.037*	0.005	*0.035*	0.011
Lagged own volatility	*0.268*	0.046	*0.097*	0.042
Lagged agg. volatility	*0.24*	0.095	*0.351*	0.092
Oil volatility	0.054	0.037	0.196	0.076
Trend	*0.3*	0.078	*0.06*	0.064
Ex. rate volatility			0.043	0.03
Mean intercept	*3.178*	1.537	*2.982*	1.576
y(-1)	*0.514*	0.28	*0.563*	0.283
y(-2)	-0.099	0.255	-0.111	0.269
Seasonal	0.012	0.022	0.009	0.028

(b) Maize (monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error variance	*0.035*	0.009	*0.04*	0.015
Random intercept	*0.016*	0.011	0.021	0.018
Lagged own volatility	*0.128*	0.071	0.051	0.035
Lagged agg. volatility	*0.3*	0.041	*0.155*	0.049
Oil volatility	*0.163*	0.054	*0.163*	0.057
Trend	*0.431*	0.059	*0.068*	0.041
Ex. rate volatility			*0.112*	0.062
Mean intercept	*1.932*	1.144	*1.958*	1.148
y(-1)	*0.765*	0.246	*0.728*	0.255
y(-2)	-0.145	0.242	-0.114	0.254
Seasonal	0.009	0.017	0.011	0.024

(c) Rice (monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error variance	*0.025*	0.007	0.026	0.009
Random intercept	*0.039*	0.007	0.038	0.009
Lagged own volatility	*0.293*	0.037	0.311	0.07
Lagged agg. volatility	*0.079*	0.025	0.118	0.071
Oil volatility	*0.095*	0.037	0.301	0.071
Trend	0.064	0.043	0.053	0.056
Ex. rate volatility			0.078	0.055
Mean intercept	*3.247*	1.588	2.975	1.79
y(-1)	*0.589*	0.257	0.677	0.299
y(-2)	-0.099	0.236	-0.144	0.277
Seasonal	-0.004	0.023	0.005	0.027

(d) Soybean (monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error variance	*0.032*	0.006	*0.035*	0.009
Random intercept	*0.03*	0.008	*0.035*	0.01
Lagged own volatility	*0.199*	0.032	*0.232*	0.073
Lagged agg. volatility	*0.369*	0.105	*0.189*	0.055
Oil volatility	0.033	0.03	0.086	0.081
Trend	0.1	0.062	*-0.236*	0.057
Ex. rate volatility			*0.201*	0.104
Mean intercept	*2.938*	1.496	*3.098*	1.602
y(-1)	*0.627*	0.271	*0.614*	0.289
y(-2)	-0.129	0.255	-0.142	0.272
Seasonal	0.006	0.021	0.005	0.027

(e) Soya Oil (monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error variance	*0.02*	0.01	0.012	0.008
Random intercept	*0.05*	0.007	0.057	0.005
Lagged own volatility	*0.226*	0.033	0.134	0.069
Lagged agg. volatility	*0.169*	0.047	0.139	0.068
Oil volatility	*0.104*	0.042	0.19	0.108
Trend	-0.076	0.057	-0.338	0.104
Ex. rate volatility			0.358	0.113
Mean intercept	*3.936*	1.592	4.621	1.78
y(-1)	*0.521*	0.229	0.469	0.244
y(-2)	-0.119	0.208	-0.168	0.223
Seasonal	-0.001	0.025	-0.009	0.031

(f) Rape (monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error variance	*0.018*	0.011	*0.018*	0.011
Random intercept	*0.055*	0.008	0.052	0.007
Lagged own volatility	*0.107*	0.039	*0.111*	0.052
Lagged agg. volatility	*0.263*	0.083	*0.244*	0.023
Oil volatility	*0.039*	0.023	0.098	0.074
Trend	*-0.296*	0.075	*-0.4*	0.079
Ex. rate volatility			0.16	0.12
Mean intercept	*4.428*	1.75	*4.412*	1.844
y(-1)	*0.522*	0.242	*0.528*	0.256
y(-2)	-0.183	0.226	-0.187	0.239
Seasonal	0.003	0.028	0.002	0.03

Table 5.2: Random parameter models: results (without stocks - continued)

(g) Palm (monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error variance	0.012	0.008	0.011	0.009
Random intercept	*0.069*	0.004	*0.069*	0.005
Lagged own volatility	*0.266*	0.044	*0.209*	0.068
Lagged agg. volatility	*0.207*	0.044	*0.186*	0.064
Oil volatility	*0.164*	0.06	*0.154*	0.066
Trend	*-0.212*	0.065	*-0.298*	0.069
Ex. rate volatility			*0.259*	0.084
Mean intercept	*4.616*	1.553	*4.67*	1.541
y(-1)	*0.433*	0.228	*0.437*	0.225
y(-2)	-0.172	0.2	-0.184	0.199
Seasonal	0.017	0.032	0.016	0.033

(h) Poultry (monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error variance	*0.005*	0.003	*0.005*	0.003
Random intercept	*0.02*	0.002	*0.02*	0.002
Lagged own volatility	*0.217*	0.038	0.095	0.069
Lagged agg. volatility	*0.115*	0.034	0.037	0.025
Oil volatility	*0.031*	0.015	*0.037*	0.018
Trend	*-0.188*	0.08	-0.149	0.111
Ex. rate volatility			*0.13*	0.048
Mean intercept	2.863	1.975	2.799	1.91
y(-1)	0.475	0.421	0.484	0.409
y(-2)	-0.118	0.387	-0.113	0.387
Seasonal	-0.012	0.022	-0.013	0.023

(i) Pigmeat (monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error variance	*0.097*	0.002	*0.098*	0.002
Random intercept	0.004	0.003	0.004	0.003
Lagged own volatility	*0.124*	0.068	*0.087*	0.029
Lagged agg. volatility	0.059	0.036	*0.062*	0.029
Oil volatility	*0.094*	0.045	*0.302*	0.046
Trend	-0.141	0.096	*-0.154*	0.047
Ex. rate volatility			*0.06*	0.036
Mean intercept	0.887	0.541	*0.895*	0.54
y(-1)	*0.868*	0.189	*0.862*	0.18
y(-2)	-0.083	0.195	-0.078	0.186
Seasonal	0.025	0.027	0.025	0.026

(j) Beef (monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error variance	*0.019*	0.009	*0.021*	0.008
Random intercept	*0.022*	0.009	*0.029*	0.007
Lagged own volatility	*0.197*	0.049	*0.259*	0.098
Lagged agg. volatility	0.055	0.041	*0.123*	0.034
Oil volatility	0.028	0.023	0.035	0.026
Trend	*0.273*	0.107	*-0.176*	0.058
Ex. rate volatility			0.050	0.041
Mean intercept	*3.261*	1.949	*3.166*	1.656
y(-1)	0.534	0.365	*0.587*	0.322
y(-2)	-0.150	0.346	-0.184	0.300
Seasonal	-0.003	0.024	0.004	0.024

(k) Butter (monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error variance	*0.056*	0.009	*0.064*	0.01
Random intercept	*0.059*	0.011	*0.058*	0.012
Lagged own volatility	*0.397*	0.107	*0.326*	0.108
Lagged agg. volatility	*0.126*	0.053	0.062	0.048
Oil volatility	*0.181*	0.104	*0.155*	0.062
Trend	0.032	0.068	*-0.288*	0.097
Ex. rate volatility			*0.16*	0.077
Mean intercept	*4.601*	1.39	*4.466*	1.517
y(-1)	0.057	0.218	0.056	0.236
y(-2)	0.052	0.198	0.038	0.22
Seasonal	0.01	0.029	0.003	0.035

(l) SMP (monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error variance	*0.037*	0.015	*0.033*	0.009
Random intercept	*0.05*	0.012	*0.038*	0.009
Lagged own volatility	*0.518*	0.146	*0.529*	0.098
Lagged agg. volatility	*0.234*	0.092	*0.12*	0.07
Oil volatility	*0.377*	0.129	*0.283*	0.097
Trend	*-0.703*	0.273	*-0.477*	0.147
Ex. rate volatility			*0.216*	0.061
Mean intercept	2.232	2.532	2.256	2.676
y(-1)	0.62	0.389	0.609	0.414
y(-2)	0.077	0.36	0.085	0.386
Seasonal	-0.001	0.029	0	0.031

Table 5.2: Random parameter models (continued)

(m) WMP (monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error variance	*0.013*	0.007	0.013	0.008
Random intercept	*0.033*	0.005	*0.035*	0.006
Lagged own volatility	*0.507*	0.1	*0.46*	0.174
Lagged agg. volatility	*0.077*	0.037	*0.156*	0.084
Oil volatility	*0.18*	0.067	*0.076*	0.032
Trend	-0.148	0.097	-0.084	0.145
Ex. rate volatility			0.337	0.213
Mean intercept	2.682	3.261	2.883	3.289
y(-1)	0.588	0.45	0.566	0.444
y(-2)	0.051	0.401	0.047	0.394
Seasonal	0.002	0.034	0.003	0.034

(n) Cheese (monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error variance	*0.014*	0.006	*0.016*	0.007
Random intercept	*0.027*	0.005	*0.026*	0.006
Lagged own volatility	*0.351*	0.062	*0.478*	0.134
Lagged agg. volatility	*0.163*	0.052	0.068	0.045
Oil volatility	*0.18*	0.026	*0.226*	0.037
Trend	-0.044	0.058	-0.068	0.105
Ex. rate volatility			*0.125*	0.075
Mean intercept	3.171	3.661	3.103	3.746
y(-1)	0.433	0.475	0.448	0.495
y(-2)	0.165	0.434	0.159	0.449
Seasonal	0.002	0.031	0.002	0.03

(o) Cocoa (monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error variance	*0.031*	0.013	*0.03*	0.014
Random intercept	*0.041*	0.012	*0.046*	0.014
Lagged own volatility	*0.2*	0.109	*0.206*	0.099
Lagged agg. volatility	*0.088*	0.048	0.037	0.032
Oil volatility	0.311	0.22	0.089	0.06
Trend	0.082	0.14	*-0.195*	0.08
Ex. rate volatility			0.083	0.059
Mean intercept	*4.633*	2.945	*4.499*	1.984
y(-1)	0.436	0.36	*0.527*	0.254
y(-2)	-0.044	0.346	-0.116	0.242
Seasonal	-0.002	0.04	0	0.03

(p) Coffee (monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error variance	*0.025*	0.007	*0.033*	0.012
Random intercept	*0.051*	0.007	*0.07*	0.01
Lagged own volatility	*0.496*	0.1	*0.492*	0.077
Lagged agg. volatility	*0.181*	0.066	0.038	0.029
Oil volatility	*0.106*	0.061	*0.108*	0.056
Trend	*0.858*	0.109	0.102	0.063
Ex. rate volatility			0.076	0.057
Mean intercept	*2.025*	1.645	*2.487*	1.318
y(-1)	*0.468*	0.266	0.393	0.262
y(-2)	0.088	0.235	0.065	0.228
Seasonal	0.011	0.021	0.027	0.036

(q) Tea (monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error variance	*0.046*	0.006	*0.037*	0.008
Random intercept	*0.044*	0.008	*0.055*	0.008
Lagged own volatility	*0.375*	0.06	*0.385*	0.1
Lagged agg. volatility	*0.085*	0.045	*0.161*	0.066
Oil volatility	0.035	0.028	0.046	0.036
Trend	*-0.098*	0.031	0.03	0.08
Ex. rate volatility			0.028	0.025
Mean intercept	*3.935*	1.292	*3.982*	1.648
y(-1)	*0.568*	0.22	*0.503*	0.267
y(-2)	-0.277	0.206	-0.222	0.243
Seasonal	0.015	0.027	0.022	0.035

(r) Sugar (monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error variance	*0.056*	0.014	*0.047*	0.02
Random intercept	*0.06*	0.015	*0.064*	0.019
Lagged own volatility	*0.251*	0.043	*0.253*	0.08
Lagged agg. volatility	*0.099*	0.048	0.088	0.061
Oil volatility	0.102	0.067	*0.141*	0.072
Trend	*-0.234*	0.047	*-0.38*	0.081
Ex. rate volatility			*0.306*	0.111
Mean intercept	*1.147*	0.513	*1.22*	0.654
y(-1)	*0.629*	0.183	*0.584*	0.219
y(-2)	-0.093	0.172	-0.078	0.205
Seasonal	0.013	0.029	0.006	0.035

Table 5.2: Random parameter models: results (without stocks - continued)

(s) Cotton (monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error variance	*0.017*	0.007	*0.039*	0.004
Random intercept	*0.023*	0.008	0.004	0.006
Lagged own volatility	*0.253*	0.12	*0.181*	0.043
Lagged agg. volatility	*0.203*	0.085	0.119	0.097
Oil volatility	*0.133*	0.048	*0.219*	0.11
Trend	*0.364*	0.134	0.004	0.047
Ex. rate volatility			*0.071*	0.037
Mean intercept	1.523	1.205	0.741	0.606
y(-1)	*0.813*	0.288	*1.156*	0.254
y(-2)	-0.198	0.272	-0.338	0.254
Seasonal	0.005	0.017	0.007	0.016

Tables 5.2 through 5.2. Two ticks in a cell indicate that the variable was significant for both models (i.e. with and without exchange rates).

Broadly speaking, the results in Table 5.5 (and Tables 5.2 through 5.2) can be summarized as follows:

1. Nearly all the commodities have significant stochastic trends (seeing as the variance in the random intercept is significant). Pork is the exception.
2. Most of the commodities have cyclical components. The exception is palm oil.
3. Past volatility is a significant predictor of current volatility for nearly all variables run over both periods (with and without exchange rate volatility). I therefore conclude that there is persistent volatility in commodity prices. That is, one would expect to see periods of relatively high volatility in agricultural commodities as well as periods of relatively low volatility.
4. There is evidence of volatility transmission across agricultural commodities for nearly all commodities (except pork). The aggregate past volatility is a predictor of volatility for most commodities. This is indicative of a situation where markets are experiencing common shocks that impact many markets rather than being isolated to one commodity or market.
5. Oil price volatility a significant predictor of volatility in agricultural commodities in the majority of series. With the growth of the biofuel sector, commodity and oil prices may become more connected, so there is reason to believe that the role of oil prices in determining volatility may be even stronger in the future.
6. As with oil prices, exchange rate volatility impacts the volatility of commodity prices for ten of the 19 series.
7. Stock levels have a significant (downward) impact on volatility for each of the three series for which data are available on stocks. This is consistent with our expectations that as stocks become lower, the markets become more volatile.
8. A number of commodity prices have significant trends. However, these trends are positive for some series and negative for others. Recent high levels of volatility in those markets should not lead us to believe that they are necessarily becoming more volatile in the long-run.

Table 5.3: Random parameter models: results (with stocks)				
	Stocks included (9 series)		Stocks not included (11 series)	
	Estimate	Stdv	Estimate	Stdv
Lagged price volatility	0.392	0.064	0.392	0.063
Export concentration	-0.07	0.104	-0.008	0.099
Yields	0.414	0.233	0.487	0.219
Exchange rate volatility	0.301	0.283	0.297	0.278
Oil price volatility	0.081	0.054	0.077	0.055
Cocoa			-0.549	0.076
Coffee	-0.363	0.102	-0.362	0.108
Tea			-0.458	0.095
Sugar	-0.148	0.068	-0.148	0.07
Cotton	-0.845	0.078	-0.845	0.08
Pooled trend	-0.083	0.042	-0.116	0.041
Trends varying across commodities				
Volatility determinants				
Lagged price volatility	0.357	0.066	0.344	0.065
Export concentration	-0.01	0.136	0.042	0.125
Yields	0.521	0.366	0.672	0.337
Exchange rate volatility	0.298	0.28	0.296	0.276
Oil price volatility	0.074	0.052	0.07	0.052
Cocoa			-0.548	0.075
Coffee	-0.361	0.101	-0.364	0.107
Tea			-0.458	0.093
Sugar	-0.148	0.068	-0.148	0.07
Cotton	-0.843	0.08	-0.844	0.084
Trends				
Wheat	-0.094	0.107	-0.122	0.105
Maize	-0.122	0.093	-0.165	0.089
Rice	-0.14	0.117	-0.195	0.111
Rapeseed	-0.231	0.123	-0.313	0.114
Palm Oil	-0.22	0.14	-0.324	0.125
Cocoa			-0.232	0.091
Coffee	0.027	0.115	0.012	0.117
Tea			-0.081	0.117

Table 5.4: Panel model results

	Wheat		Maize		Soybeans	
Parameter	Mean	Stdv	Mean	Stdv	Mean	Stdv
Error variance	0.019	0.011	0.04	0.01	0.016	0.008
NON STATIONARY						
Lagged own volatility	0.1	0.071	0.064	0.039	0.076	0.066
Lagged aggregate volatility	0.02	0.017	0.109	0.07	0.101	0.054
Stocks	-0.11	0.031	-0.128	0.073	-0.324	0.111
Trend	0.338	0.164	0.441	0.164	0.045	0.035
Exchange rate vol	0.238	0.124	0.34	0.124	0.059	0.049
Oil price vol	0.1	0.071	0.064	0.039	0.076	0.066
AUTOREGRESSIVE						
Mean intercept	3.274	1.773	1.538	1.569	4.009	1.86
y(-1)	0.459	0.293	0.712	0.365	0.488	0.287
y(-2)	-0.059	0.278	-0.02	0.366	-0.109	0.272
Seasonal	-0.014	0.03	0.015	0.031	-0.006	0.029

Annual results

The annual results were produced using the panel approach and are presented in Table 5.4. There are four sets of results. The first two are those with and without the inclusion of stocks (this is because the stocks data cover a shorter period of time than the commodity price data). For the next two sets I restricted the trends in the panel regression so that in one they were the same across each of the commodities, while in another they were allowed to vary.

Where stocks are included, they are significant for the model in which the trend is restricted, but become insignificant when the trends in volatility are allowed to vary for each of the commodities. Notably, the estimated trends are generally negative, and the restriction of common trends across the commodities seems reasonable. Thus, the results do suggest (as with the higher frequency data) that as stocks rise, the level of volatility in prices decreases.

As with the higher frequency data, there is strong evidence of persistence in volatility. This finding is robust to the specification of the model, seeing as lagged volatility is significant in all four specifications. Yields also appear to be a significant determinant of volatility. In each of the four specifications, higher yields lead to larger volatility in the series. As argued earlier, there is no clear case for expecting yields to have a positive or negative influence on volatility in the first instance. Obviously, one would expect high yields to drive prices down and low yields to drive prices up. However, this does not imply the volatility of the series should go up or down. Our results suggest that high yields have a tendency to drive prices downwards to a greater extent than low yields drive prices up. While I do not investigate this further here, it is also possible that the response to yields is dependent on the level of stocks.

Finally, unlike the higher frequency data, there is only weak evidence that oil price volatility and exchange rate volatility have an impact on the volatility of commodity prices.

Table 5.5: Summary of results

		Error variance	Random intercept variance	Past own volatility	Lag aggregate volatility	Oil volatility	Trend	Ex. rate volatility	Stocks
2	Wheat	√√	√√	√√	√√		√(+)√(+)		√
3	Maize	√√	√	√	√√	√√	√(+)√(+)	√	√
5	Soybeans	√√	√√	√√	√√		√(-)	√	√
6	Soya oil	√	√√	√√	√√	√√	√(-)	√	n/a
7	Rape	√√	√	√√	√√	√	√(-)√(-)		n/a
8	Palm		√√	√√	√√	√√	√(-)√(-)	√	n/a
9	Poultry	√√	√√	√	√	√	√(-)	√	n/a
17	Coffee	√√	√√	√√	√	√√			n/a
18	Tea	√√	√√	√√	√√		√(-)		n/a
19	Sugar	√√	√√	√√	√	√	√(-)√(-)		n/a
20	Cotton	√√	√	√√	√	√√	√(+)	√	n/a

Conclusions

Several important findings emerge from our empirical study. First, there is strong evidence of persistent volatility in agricultural series. Nearly all of the series examined showed that variance was a function of past volatility, and this finding was robust to the choice of model and frequency of data. Next, there was convincing evidence that some degree of volatility transmission exists across commodities in monthly data. Where stocks and yield data were available, these also appeared to be significant determinants of the volatility of agricultural commodity prices.

There is also convincing evidence that many of the candidate variables have an impact on volatility. In monthly series, oil price volatility had a positive impact on commodity price volatility. Thus, from the evidence available, the recent coincidence of high volatility in both oil and commodity prices is symptomatic of a connection between the two. As discussed above, this link is likely to continue thanks to the impact of energy prices on the costs of production along with the alternative use of some crops for biofuel production. Therefore, one would expect the link between oil and agricultural price volatility to continue or strengthen as the biofuels sector grows. Likewise, exchange rate volatility was found to influence agricultural prices. Thus, perhaps unsurprisingly, if the global economy is experiencing high levels of volatility, it will be reflected in agricultural prices, even though no significant link between export concentration (as measured by the Herfindahl index) and oil price volatility was identified.

Finally, the evidence produced in this chapter suggests that agricultural price volatility contains trends that are independent of the variables used here to explain volatility. However, the evidence is mixed with regard to the direction of these changes. In the monthly data, these trends were positive for some commodities and negative for others. For the annual data, the evidence shows that the trends were, having accounted for oil price volatility and other factors, negative. Thus, our overall results do not predict increasing volatility in agricultural markets unless there is increasing volatility in the variables that determine that volatility. On the other hand, if factors such as oil prices continue to be volatile, agricultural prices may begin or continue to reflect that volatility.

References

Aizeman, J. & Pinto, B. 2005. *Managing Economic Volatility and Crisis, A practitioners Guide*. Cambridge University Press, World Bank, New York.

Balcombe, K. & Rapsomanikis, G. 2008. Bayesian estimation and selection of nonlinear vector error correction models: The case of the sugar-ethanol-oil nexus in Brazil, *American Journal of Agricultural Economics*, 90(3): 658–668.

Chib, C. & Greenberg, E. 1995. Understanding the Metropolis-Hastings algorithm, *The American Statistician*, 49(4): 327–335.

Deaton, A. & Laroque, G. 1992. On the behaviour of commodity prices, *Review of Economic Studies*, 59(1): 1–23.

Engle, R. F. 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation, *Econometrica*, 50(4): 987–1007.

——— 1995. *ARCH, Selected Readings. Advanced Texts in Econometrics.* Oxford, Oxford University Press.

FAO 2008. *Food Outlook, June issue,* Rome.

Harvey, A. 1989. *Forecasting structural time series models and the Kalman filter*. Cambridge, Cambridge University Press.

Harvey, P. 2007. *Cash-based responses in emergencies,* Overseas Development Institute, London.

Koop, G. 2003. *Bayesian Econometrics*. Wiley, Sussex.

Oxley, L., Donald, A., Colin, J. & Sayer, S. 1994. *Surveys in Econometrics*. Wiley Blackwell.

Train, K. 2003. *Discrete Choice Methods with Simulation*. Cambridge University Press.