The Nature and Determinants of Volatility in Agricultural Prices

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An Empirical Study from 1962-2008

The volatility of 19 agricultural commodity prices are examined at monthly and annual frequencies. All of the price series are found to exhibit persistent volatility (periods of relatively high and low volatility). There is also strong evidence of transmission of volatilities across prices. Volatility in oil prices is found to be a significant determinant of volatilities in the majority of series and, likewise, exchange rate volatility is found to be a predictor of volatility in over half the series. There is also strong evidence that stock levels and yields are influencing price volatility. Most series exhibit significant evidence of trends in their volatility. However, these are in a downward direction for some series and in an upward direction for other series. Thus, there is no general finding of long term increases in volatility across most agricultural prices

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1. Introduction

There is now considerable empirical evidence that the volatility in agricultural prices has changed over the recent decade (FAO, 2008). Increasing volatility is a concern for agricultural producers and 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. Arguably, higher volatility results in an overall welfare loss (Aizeman and Pinto, 2005)[2], 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 markets and/or countries. Therefore, an understanding the nature of volatility is therefore required in order to mitigate its effects, particularly in developing countries, and further empirical work is needed to enhance our current understanding. In view of this need, the work described in this report, seeks to study the volatility of a wide range of agricultural prices.

Importantly, when studying volatility, the primary aim is not to describe the trajectory of the series itself, or to describe the determinants of directional movements of the series, but rather to describe the determinants of the absolute or squared changes in the agricultural prices[3]. We approach this problem from two directions: First, by directly taking a measure of the volatility of the series and regressing it against a set of variables such as stocks, or past volatility etc.; Second, by modelling the behaviour of the series[4], while examining whether the variances of the shocks that drive the evolution of prices can be explained by past volatility and other key variables.

More specifically, we 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. Volatility for each of these components is then examined. Using this approach we ask whether volatility in each price series is predictable, and whether the volatility of a given price is dependent on stocks, yields, export concentration and the volatility of other prices including oil prices, exchange rates and interest rates. This first approach will be used to analyse monthly prices[5]. The second approach uses a panel regression approach where volatility is explained by a number of key variables. This second approach will be used for annual data, since the available annual series are relatively short.

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

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[2] For a coverage of the literature relating the relationship between welfare, growth and volatility, readers are again referred the Aizeman and Pinto, 2005, page 14 for a number of classic references on this topic.

[3] 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.

[4] This is done using a 'state space form' which is outlined in a technical appendix

[5] Data of varying frequencies is not used for theoretical reasons, but due to the data availability. These were provided by FAO.

The report proceeds as follows. Section 2 gives a quick review of some background issues regarding volatility. This report does not discuss the consequences of volatility. Its aim is limited to conducting an empirical study into the nature and causes of volatility, and to explore whether these have evolved over the past few decades. To this purpose, Section 3 outlines the theoretical models that are used for the analysis. Section 4 outlines the estimation methodology, and Section 5 presents the empirical results, with tables being attached in Appendix A. Section 6 concludes. Mathematical and statistical details are left to a technical appendix (Appendix B).

2. Background

2.1. Defining volatility

While the volatility of a time series may seem a rather obvious concept, there may be several different potential measures of the volatility of a series. For example, if a price series has a mean[6], then the volatility of the series may be interpreted as its tendency to have values very far from this mean. Alternatively, the volatility of the series may be interpreted as its tendency to have large changes in its values from period to period. A high volatility according to the first measure need not imply a high volatility according to the second. Another commonly used 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[7]. Thus, a universal measure of what seems to be a simple concept is 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 does 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 this is 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 where it is highly volatile. The existence of the periodic form of volatility is now well established empirically 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 are 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 that changes in volatility are exhibited in markets for agricultural commodities, there is still 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 (1992) present models based on the theories of competitive storage that suggest, inter alia, that variations in the volatility of prices should exist. Moreover, market

[6] That is, the underlying data generating process has a mean, not just the data in the sample.
[7] This definition is embodied in the notion of ‘implied volatility’, whereby futures or options prices relative to spot prices are used to measure volatility.

traders are to some extent acting in a similar way to the agents that determine financial series. They are required to buy and sell according to conditions that are changeable, and there is money to be made by buying and selling at the right time. However, agricultural commodities prices are different from most financial series since the levels of production of these commodities along with the levels of stocks are likely to be an important factor in the determination of their prices (and the volatility of these prices) at a given time. The connectedness of agricultural markets with other markets (such as energy) that may also be experiencing variations in volatility may influence the volatility of agricultural commodities.

For a series that has a stable mean value over time (mean reverting[8]), the variance of that series would seem to be obvious statistic that describes the **ex ante** (forward looking) volatility of a given series[9]. More generally, if a series can be decomposed into components such as trend and cycle, the variance of each of these components can describe the volatility of the series. The use of the words **ex ante** requires emphasis, because clearly a price series can have relatively large and small deviations from its mean without implying that there is a shift in its overall variability. It is important to distinguishing between ex post (historical or backward looking) volatility and ex ante (forward 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.[10] 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 are more likely to behave in a way where there are periods of substantial instability. It is for this reason that we are primarily interested in ex ante volatility, and whether we can predict changes in ex ante volatility using historical data.

A wide range of models that deal with systematic volatility have been developed since the seminal proposed by Engle (1982)[11]. Since then, the vast majority of volatility work has often focused on series that where the trajectory of the series 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, for many other series (such as agricultural prices) this may not really be appropriate, as there is evidence that these series are cyclical, sometimes with, or without, trends that require modelling within a flexible and unified framework. Deaton and Laroque (1992), citing earlier papers, note that many commodity prices also behave in a manner that is 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, we would emphasis 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 these components. Therefore, the approach adopted within this report allows for

[8] 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.

[9] If the series has a distribution with ‘fat tails’, even the variance may give an inaccurate picture of the overall volatility of a series.

[10] For this reason, some writers make the distinction between the realised and the implied volatility of a series.

[11] For a number of papers on this topic, see Engle R. (1995) and the Survey article in Oxley et al. (2005)

changes in the volatilities of both components should they exist, 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 before, they may 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, we take the view that volatility can be a problem, even if large changes could have been anticipated given past information. This viewpoint underpins the definitions of volatility employed within this study.

The definitions of volatility employed within this study are also influenced by the frequencies of the available data (the data is discussed in Section 5). Since we have price data at the monthly frequency for the majority of series, but a number of explanatory variables at the annual frequency, we need to create a measure of annual volatility using the monthly price data. 'Annual volatility' should not just be defined by the difference between the price at the beginning of the year and the end. Any measure should take account of the variability within the year. Therefore, to create the annual volatility measures we take yearly volatility to be the log of the square root of the sum of the squared percentage changes in the monthly series. Admittedly, this measure is one possible measure among many. However, it is a convenient summary statistic that is approximately normally distributed, and therefore usable within a panel regression framework. This statistic is an ex-post measure of volatility. Changes in this statistic, year to year, 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 are likely to be reflected in this measure.

When focusing on the higher frequency data, this study then defines volatility as a function of the variance of the random shocks that drive the series, along with the serial correlation in the series. This volatility is then decomposed into components: 'cyclical'; and 'level'. Within this approach, volatility is not just defined in terms of ex-post changes in the series, but in the underlying variance of the shocks governing the volatility of series. The influence of other variables on these variances can be estimated using this method. Our approach is outlined at a general level in Section 3 (the decomposition approach), and at a more mathematical level in a technical appendix.

Before proceeding, it is also worth noting that there are some further aspects of price behaviour that are not directly explored within this report. Other 'stylised facts' relating to commodity prices are that commodity price distributions may have the properties of 'skew' and 'kurtosis'. The former (skew) suggests that prices can reach occasional high levels, that are not symmetrically matched by corresponding lows, with prices spending longer in the 'doldrums' than at higher levels (Deaton and Laroque, 1992). The latter (kurtosis) suggest that extreme values can occur occasionally. Measurements of skew and kurtosis of price distributions can be extremely difficult to establish when the prices contain cycles and/or trends, and have time varying volatility. Some of the previous empirical work that supports the existence of the skew and kurtosis has been extremely restrictive in the way that it has modelled the series (e.g. such as assuming 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 we may be able to account for the apparent skew in the distributions of prices. Thus, some of the other 'stylised facts' may in reality be a by product of systematic variations in volatility.

2.2 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 (Den et al., in Aizeman and Pinto, Chapter 4, 2005). If indeed this a major reason for volatility then we should see a change in the degree of volatility as the 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 over time. 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 demonstrate a shift in the average volatility of many agricultural prices, and this is further supported by evidence on implied volatility (FAO 2008). This is against the backdrop of a general shift towards market liberalisation and global markets, along with dramatic changes in the energy sector with an increasing production of biofuels. We consider the factors listed below, each with a short justification. Due to data constraints, we are unable to include all factors in the same models over the whole period. Therefore, a subset of these factors enter each of the models, depending the frequency of the data used in estimation.

Past Volatility: The principles underlying autoregressive conditional heteroscedasticity (ARCH) and its generalised forms (e.g. GARCH) posit that there are periods of relatively high and low volatility, though the underlying unconditional volatility remains unchanged. Evidence of ARCH and GARCH is widespread in series that are partly driven by speculative forces. Accordingly, these may also be present the behaviour of agricultural prices.

Trends: There may be long run increases or decreases in the volatility of the series. These will be accounted for by including a time trend in the variables that explain volatility. 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 the stocks of commodities fall, it is expected that the volatility in the prices would increase. If stocks are low, then the dependence on current production in order to meet short term consumption demands would be 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 and 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: The yield for a given crop may obviously drive the price for a given commodity up or down. A particularly large yield (relative to expectations) may drive prices down, and a particularly low yield may drive prices up. However, in this report we are concerned not with the direction of change but on the impact on the absolute magnitude of these changes. If prices respond symmetrically to yields then we might expect no impact on the volatility of the series. However, if a large yield has a bigger impact on prices and a low yield, then we might expect that volatilities are positively related to yields, and conversely if a low yield has a bigger impact on prices that a high yield then volatilities are negatively related to yields. A priori, it is difficult to say in which direction yields are likely to push volatility, if they influence the level of volatility at all. For example, a high yield may have a dramatic downward pressure on price (downwards, increasing volatility). However, this higher yield may lead to larger stocks in the next year (decreasing volatility in a subsequent period).

Transmission across prices: A positive transmission of volatility of prices 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 on 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 a big 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 the production of biofuels. Recent empirical work has suggested a transmission of prices between oil and sugar prices (Balcombe and Rapsomanikis, 2005). There is also likely to be a strong link between input costs and output prices. Fertiliser prices, mechanised 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 oil price has shown unprecedented realised volatility over the past few years, there is clearly the potential for this volatility to spill over into the volatility of commodity prices.

Export Concentration: Fewer countries exporting could expose international markets to variability in their exportable supplies, weather shocks and domestic events such as policy changes. Lower Herfindahl (the index used here) concentration 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, since they represent a cost to holding of stocks. However, they are also an important indicator of economic conditions. Volatility of interest rates may therefore indicate uncertain economic conditions and subsequent demand for commodities.

3 Models

This section will outline at a general level the main elements of the models used for analysis. The mathematical details behind the models outlined in this section are contained in an appendix. As outlined in the preceding sections, there are two main methods of analysis used within this report. Each is dealt with below.

3.1 The decomposition approach

At the heart of this approach is the decomposition for the logged price y_t at time t as in equation (3) below.

$$y_t = Level_t + Seasonal_t + Cycle_t \qquad (3)$$

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 are assumed to be random shocks, governed by a time varying variances h_{vt} and h_{et} respectively. Either one of these variances may be zero for a given price, but both cannot be zero since this would imply that the series had no random variation. For the level component, a variance of zero would imply a constant mean for the series, and therefore 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). Two different methods of modelling the seasonality were explored. First 'seasonal dummies' were employed, whereby the series is allowed a seasonal component in each month. Alternatively, the seasonal frequency approach from Harvey (1989 p.41) was employed. 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, the results that are presented in the empirical section use the first seasonal frequency only.

The Level and Cyclical components have variance, which we label as follows:

$$Var(\Delta Level_t):\ volatility\ in\ mean$$

$$Var(Cycle):\ volatility\ in\ cycle$$

Each of these are governed by an underlying volatility of a shock specific to each component, and can (within the models outlined in the appendix) shown to be

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

Having made this decomposition, then we can make h_{vt} and h_{et} depend on explanatory variables. Within this report we consider the following explanatory variables for the volatilities, which we have discussed earlier in Section 2:

i) a measure of the past realised volatility of the series ;
ii) realised oil price volatility;
iii) a measure of the average realised volatility in the other agricultural prices within the data;
iv) stocks levels;
v) realised exchange rate volatility;
vi) realised interest rate volatility; and,
vii) a time trend;

In each case where we use the term 'realised' volatility, the measure will 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, we then produce:

i) measures in volatility (mean and cycle) for each of the agricultural price series through time;
ii) tests for the persistence in the changes in volatility for these series;
iii) tests for the transmission of volatility across price series; and;
iv) tests for the transmission of volatility from oil prices, stocks etc to agricultural prices.

3.2 The panel approach

In order complement the approach above, use of annual data is also made. A panel approach is used due to the relatively short series available (overlapping across all the variables) at the annual frequency. The following approach is employed[12]:

$$lnV_{it} = \beta_{0i} + \beta_{1i}t + \lambda_v lnV_{i(t-1)} + \lambda' z_{it} + e_{it} \qquad (4)$$

Where V_{it} is a (realised) 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 be normal with a variance that is potentially different across the commodities, serially independent, but with a covariance across *i* (commodities). We 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[13].

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

[13] 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.

Within z_{it} we consider the following:

i) realised oil price volatility;
ii) stocks;
iii) yields;
iv) realised exchange rate volatility; and,
v) realised export concentration (the Herfindhal index);

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

$$V_{it} = \sqrt{\frac{\sum_{j=1}^{12} \quad (\Delta \ln(p_{i.j.t}))^2}{12}} \qquad (5)$$

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 summarises 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 give similar results within a regression framework. The logged measure of volatility (as defined in 5) is approximately normally distributed for the annual series used in this report, which it attractive from an estimation point of view.

4 Estimation and interpretation

4.1 Estimation

The work in this study employs a Baeysian approach to estimation. The reason for using a Bayesian framework is that it is a more robust method of estimation in the current context. The estimation of the random parameter models can be performed using the Kalman Filter (Harvey 1989). 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.

A full description of the estimation procedures are beyond the scope of this report as while many of the methods are now standard within Bayesian econometrics, a full description would run into many pages. Good starting references include Chib and Greenberg (1995) and Koop (2003). A brief coverage of the estimation procedures is given in the technical appendix (B2).

4.2 Interpretation of the parameter estimates and standard deviations

In interpreting the estimates produced in this report, readers may essentially adopt a classical approach (the statistical approach with which most readers are more likely to be familiar). Strictly speaking, the Bayesian approach requires some subtle differences in thinking. However, there are theoretical results (see Train, 2003) establishing that using the mean of the posterior (the Bayesian

Stochastic trends could exist in the stocks, yield and export concentration data, and we recognise therefore these could have an influence on the results.

estimate of a parameter) is equivalent to the 'maximum likelihood' estimate (one of the most commonly used classical estimate), sharing the property of asymptotic efficiency. As the sample size increases and the posterior distribution normalises, 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, we 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 the results section). Broadly speaking, if the estimate is twice as large as its standard deviation then this is roughly consistent with that estimate being statistically significant at the 5% level.

5 Empirical Results

5.1 Data

The data for this study were provided by FAO. A summary of the length and frequency of the data is provided in Table 1. The models discussed in the previous section will be estimated using this data. The first set of models outlined in section 3 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 are recorded over a shorter period that others, the models will be run using a subset of the data for longer periods and all of the variables for longer periods. Where stocks are used in the models, at a monthly frequency, they were interpolated from the quarterly data, but the models were estimated at the shorter frequency.[14]

5.2 Results

5.2.1 Monthly results.

We 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, since these were available only from 1973 onwards (see Table 1). The models using monthly data were then re-estimated including exchange rates (over the shorter period). When running the models, we 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 2 to 21. 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, since exchange rates were only available from 1973 onwards. The difference in the parameter values will therefore differ due to this as well as the inclusion of exchange rates. Table 21 presents the monthly results for the three series for which stocks data are available.

[14] Weekly prices also exist for a few commodities only. We did analyse this data, but the results were rather inconclusive. Our analysis of this data are not included in this report but are available.

In Tables 2 through 24, the error variance refers to the square root estimate of the intercept for h_e as defined in Section 3. The Random intercept variance is the square root of intercept estimate of h_v. The rest of the parameter estimates are the lambda parameters in equations $b10$ and $b11$ (in Appendix B) where these are the coefficients of the variables listed in the first column of each table. The last four coefficients in each table are: 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 being in bold italics indicating that the standard deviation is less than 1.64 of the absolute mean of the posterior distribution. As noted in Section 4.2, this roughly corresponds to a variable being significant at the 5% level (one tailed).

While the focus of our analysis is mainly on the determinants of the volatility of the series, it is worth nothing 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. However having said this, the majority of the series have negative second order coefficients suggesting that the majority of the series contain cyclical behaviour. The seasonal components of the series are insignificant for nearly all commodities.[15] While the second order coefficient and seasonal components could be removed, an exploratory analysis suggested that inclusion of these components had not substantive impact on the results. Therefore, for consistency, these explanatory variables are included for all the series.

Table 23 summarises the results for the monthly data, from Tables 2 through 21. Each series has two sets of results in tables 2 through 20. 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 variable is included and they are run over different periods. The stocks data was available for only 3 of the series (Wheat, Maize and Soyabean). Therefore, there is another table (21) which utilises the stocks data. Again, this is run over a shorter period than for all the previous results, since the stocks data is only available from the periods listed in Table 1. The rest of the column in in Table 1 is blacked out for the other commodities for which stocks data is 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 models in Tables 2 through 20. Two ticks in a cell indicate that the variable was significant for both the models (i.e. with and without exchange rates).

Broadly, the results in Table 23 (and Tables 2 through 21) can be summarised as follows:

i) Nearly all the commodities have significant stochastic trends (as the variance in the random intercept is significant). Pigmeat is the exception.
ii) Most of the commodities have cylcial components with the exception of palm oIl.

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

iii) Past volatility is a significant predictor of current volatility for nearly all variables run over both periods (with and without exchange rate volatility). We therefore conclude that there is persistent volatility in commodity prices. That is, we would expect to see periods of relatively high volatility in agricultural commodities and periods of relatively low volatility.

iv) There is evidence that there is transmission of volatility across agricultural commodities for nearly all commodities (except pigmeat). The aggregate past volatility is a predictor of volatility in most commodities. This is indicative of a situation where markets are experience common shocks that impact on many markets rather than being isolated to one commodity or market.

v) Oil price volatility a significant predictor of volatility in agricultural commodities in the majority series. With the growth of the biofuel sector, commodity prices and oil prices may become more connected, so there is reason to believe that the role of oil prices in determining volatility may even be stronger in the future.

vi) As with oil prices, exchange Rate volatility impacts on the volatility of commodity prices for 10 out of the 19 series.

vii) Stock levels have a significant (downward) impact on the volatility for each of the three series for which we have data on stocks. This is consistent with our expectations that as stocks become lower, the markets become more volatile.

viii) 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 should not lead us to believe that agricultural markets are necessarily becoming more volatile in the long run.

5.2.2 Annual results

The annual results were produced using the panel approach outlined in Section 3.2 and are presented in Table 22. Four sets of results are presented within that table. First, results are produced with and without the inclusion of stocks. This is because the stocks data was for a shorter period than for the commodity price data. Next, we allowed for the trends in the panel regression to be restricted to be the same across each of the commodities, and in another model they were allowed to vary, giving four sets of results overall.

Where stocks are included, stocks are significant for the model in which the trend is restricted, but becomes 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 the prices decreases.

As with the higher frequency data, there is strong evidence that there is persistence in volatility. This finding is robust to the specification of the model since 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 in Section 2.3, there is no clear case for expecting yields to have a positive or negative influence on volatility in the first instance. Obviously, we 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 tend to drive prices up. While we 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.

6 Conclusions

Several important findings emerge from our empirical study. First, there is strong evidence that there is persistent volatility in agricultural series. In nearly all of the series examined, there was evidence that the variance of the series was a function of the past volatility of the series, and this finding was robust to the choice of model and frequency of the data. Next, there was convincing evidence that there was some degree of transmission of volatility across commodities in the 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 coincidental high volatility in oil and commodity prices is symptomatic of a connection between commodity price volatility and oil price volatility. As discussed earlier. the link between oil prices and agricultural commodity prices is likely to arise through the impact of energy prices on the costs of production, along with the alternative use of some crops for biofuel production. Therefore, we would expect the link between oil price volatility and agricultural prices to continue or strengthen as the biofuels sector grows. Likewise, exchange rate volatility was found to influence the volatility of agricultural prices. Thus, perhaps unsurprisingly, if the global economy is experiencing high levels of volatility these will also be reflected in agricultural prices. Although, in this study we could not identify any significant link between export concentration (as measured by the Herfindahl index) and oil price volatility.

Finally, the evidence produced in this report also suggested volatility of agricultural prices contained trends that were independent of the variables used to explain volatility in this report. 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 was that the trends were, having accounted for oil price volatility and other factors, negative. Thus, overall the results here do not suggest that there will be increasing volatility in agricultural markets unless there is increasing volatility in the variables that are determining that volatility. On the other hand, if factors such as oil prices continue to be volatile, then agricultural prices may continue to be volatile or become increasingly volatile.

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Appendix A: Tables

Table 1. Data Series Summary

	Frequency	Annual	Annual	Annnual	Monthly	Quarterly
	Series	Stocks	Yeild	Herfindel	Price	Stocks
Commodity						
Wheat	1	1962-2007	1962-2007	1961-2006	Jan 57-Mar09	June:1977-Dec2008
Maize	2	1962-2007	1962-2007	1961-2006	Jan 57-Mar09	June1975:June2008
Rice, Milled	3	1962-2007	1962-2007	1961-2006	Jan 57-Mar09	
Oilseed, Soybean	4	1962-2007	1962-2007	1961-2006	Jan 57-Jan09	Dec1990:Dec:2008
Oil, Soybean	5	1962-2007		1961-2006	Jan 57-Jan09	
Oil, Rapeseed	6	1962-2007	1962-2007	1961-2006	Jan70-Jan09	
Oil, Palm	7	1962-2007	1962-2007	1961-2006	Jan60-Jan09	
Poultry, Meat, Broiler	8	1962-2007		1961-2006	Feb80-Nov08	
Meat, Swine	9	1962-2007		1961-2006	Feb80-Nov08	
Meat, Beef and Veal	10	1962-2007		1961-2006	Jan57-Oct08	
Dairy, Butter	11	1962-2007		1961-2006	Jan57-Jan09	
Dairy, Milk, Nonfat Dry	12	1962-2007		1961-2006	Jan90-Jan09	
Dairy, Dry Whole Milk Powder	13	1962-2007		1961-2006	Jan90-Jan09	
Dairy, Cheese	14	1962-2007		1961-2006	Jan90-Jan09	
Cocoa	15		1962-2007	1961-2006	Jan57-Nov08	
Coffee, Green	16	1962-2007	1962-2007	1961-2006	Jan57-Nov08	
Tea	17		1962-2007	1961-2006	Jan57-Nov08	
Sugar	18	1962-2007	1962-2007	1961-2006	Jan57-Nov08	
Cotton	19	1962-2007	1962-2007	1961-2006	Jan57-Nov08	

Other Data	Frequency				Monthly	
Oil Prices					Jan 57-Mar09	
Exchange Rates					1973-2007	
Interest Rates (US 6 month Treasury Bill)						

Tables: Monthly Data

Table 2. Wheat (Monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error Variance	***0.02***	0.007	***0.029***	0.01
Random intercept variance	***0.037***	0.005	***0.035***	0.011
Lagged Own Volatility	***0.268***	0.046	***0.097***	0.042
Lagged AggVolatility	***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

Table 3. 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 AggVolatility	***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

Table 4. Rice (Monthly)

Parameter	Mean	Stdv	***Mean***	Stdv
Error Variance	***0.025***	0.007	***0.026***	0.009
Random intercept variance	***0.039***	0.007	***0.038***	0.009
Lagged Own Volatility	***0.293***	0.037	***0.311***	0.07
Lagged AggVolatility	***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

Table 5. Soyabean (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 AggVolatility	***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

Table 6. Soya Oil (Monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error Variance	***0.02***	0.01	0.012	0.008
Random intercept variance	***0.05***	0.007	***0.057***	0.005
Lagged Own Volatility	***0.226***	0.033	***0.134***	0.069
Lagged AggVolatility	***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

Table 7. 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 AggVolatility	***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 8. Palm (Monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error Variance	0.012	0.008	0.011	0.009
Random intercept variance	***0.069***	0.004	***0.069***	0.005
Lagged Own Volatility	***0.266***	0.044	***0.209***	0.068
Lagged AggVolatility	***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

Table 9. 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 AggVolatility	***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

Table 10. Pigmeat (Monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error Variance	***0.097***	0.002	***0.098***	0.002
Random intercept variance	0.004	0.003	0.004	0.003
Lagged Own Volatility	***0.124***	0.068	***0.087***	0.029
Lagged AggVolatility	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

Table 11. 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 AggVolatility	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

Table 12. Butter (Monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error Variance	***0.056***	0.009	***0.064***	0.01
Random intercept variance	***0.059***	0.011	***0.058***	0.012
Lagged Own Volatility	***0.397***	0.107	***0.326***	0.108
Lagged AggVolatility	***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

Table 13. 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 AggVolatility	***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 14. WMP (Monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error Variance	***0.013***	0.007	0.013	0.008
Random intercept variance	***0.033***	0.005	***0.035***	0.006
Lagged Own Volatility	***0.507***	0.1	***0.46***	0.174
Lagged AggVolatility	***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

Table 15. 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 AggVolatility	***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

Table 16. Cocoa (Monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error Variance	***0.031***	0.013	***0.03***	0.014
Random intercept variance	***0.041***	0.012	***0.046***	0.014
Lagged Own Volatility	***0.2***	0.109	***0.206***	0.099
Lagged AggVolatility	***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

Table 17. 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 AggVolatility	***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

Table 18. Tea (Monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error Variance	***0.046***	0.006	***0.037***	0.008
Random intercept variance	***0.044***	0.008	***0.055***	0.008
Lagged Own Volatility	***0.375***	0.06	***0.385***	0.1
Lagged AggVolatility	***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

Table 19. 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 AggVolatility	***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 20. Cotton (Monthly)

Parameter	Mean	Stdv	Mean	Stdv
Error Variance	***0.017***	0.007	***0.039***	0.004
Random intercept variance	***0.023***	0.008	0.004	0.006
Lagged Own Volatility	***0.253***	0.12	***0.181***	0.043
Lagged AggVolatility	***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

Table 21. (Monthly with Stocks)

	Wheat		Maize		Soyabean	
Parameter	Mean	Stdv	Mean	Stdv	Mean	Stdv
Error variance	***0.019***	0.011	***0.04***	0.01	***0.016***	0.008
Random intercept	***0.037***	0.01	0.017	0.013	***0.043***	0.006
Lagged Own Volatility	0.1	0.071	***0.064***	0.039	0.076	0.066
Lagged Aggregate	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
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

Table 22. Panel Results

Stocks Included (9 Commodities)			Stocks Not Included	
(9 Commodities)			(11 Commodities)	
	Estimate	Stdv	Estimate	Stdv
Lagged price volatility	***0.392***	0.064	***0.392***	0.063
Stock levels	***-0.103***	0.055		
Export concentration	-0.07	0.104	-0.008	0.099
Yeilds	***0.414***	0.233	***0.487***	0.219
Exchange rate	0.301	0.283	0.297	0.278
Oil Price Volatility	0.081	0.054	0.077	0.055
Intercepts				
Wheat	***-0.834***	0.064	***-0.833***	0.07
Maize	***-0.764***	0.057	***-0.763***	0.061
Rice	***-0.85***	0.091	***-0.852***	0.093
Soybeans	***-0.793***	0.074	***-0.794***	0.08
Rapeseed	***-0.647***	0.076	***-0.649***	0.086
Palm Oil	***-0.454***	0.076	***-0.457***	0.086
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				
Volatility				
Lagged price volatility	***0.357***	0.066	***0.344***	0.065
Stock levels	-0.075	0.054		
Export concentration	-0.01	0.136	0.042	0.125
Yeilds	***0.521***	0.366	***0.672***	0.337
Exchange rate	0.298	0.28	0.296	0.276
Oil Price Volatility	0.074	0.052	0.07	0.052
Intercepts				
Wheat	***-0.833***	0.067	***-0.833***	0.072
Maize	***-0.765***	0.06	***-0.763***	0.062
Rice	***-0.853***	0.093	***-0.854***	0.094
Soybeans	***-0.794***	0.075	***-0.793***	0.081
Rapeseed	***-0.647***	0.076	***-0.647***	0.082
Palm Oil	***-0.455***	0.077	***-0.455***	0.083
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
Soybeans	-0.129	0.112	***-0.192***	0.102
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
Sugar	***-0.164***	0.076	***-0.196***	0.075
Cotton	-0.098	0.103	***-0.146***	0.101

Table 23	Summary of Monthly Data								
	Summary of Monthly Data	Error Variance	Random Intercept Variance	Past Own Volility	Lag Aggregate Volatity	Oil Volatility	Trend	Exrate Vol	Stocks
2	Wheat	√√	√√	√√	√√		√(+)√(+)		√
3	Maize	√√	√	√	√√	√√	√(+)√(+)	√	√
4	Rice	√√	√√	√√	√√	√√			
5	Soyabean	√√	√√	√√	√√		√(-)	√	√
6	Soya Oil	√	√√	√√	√√	√√	√(-)	√	
7	Rape	√√	√	√√	√√	√	√(-)√(-)		
8	Palm		√√	√√	√√	√√	√(-)√(-)	√	
9	Poultry	√√	√√	√	√	√	√(-)	√	
10	Pigmeat	√√		√√		√√	√(-)	√	
11	Beef	√√	√√	√√	√		√(+)√(-)		
12	Butter	√√	√√	√√	√	√√	√(-)	√	
13	SMP	√√	√√	√√	√√	√√	√(-)√(-)	√	
14	WMP	√	√√	√√	√√	√√			
15	Cheese	√√	√√	√√	√	√√	√(-)	√	
16	Cocoa	√√	√√	√√	√√				
17	Coffee	√√	√√	√√	√	√√			
18	Tea	√√	√√	√√	√√		√(-)		
19	Sugar	√√	√√	√√	√	√	√(-)√(-)		
20	Cotton	√√	√	√√	√	√√	√(+)	√	

Appendix B: Technical Appendix

B1 Random Parameter Models with Time Varying Volatility

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

$$\theta(L)y_t = \alpha_t + \delta' d_t + e_t \qquad (b1)$$

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

$$\alpha_t = \alpha_{t-1} + v_t \qquad (b2)$$

where d_t is a vector of deterministic variables[16] 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:

$$y_t = Level_t + Seasonal_t + Cycle_t \qquad (b3)$$

$$Level\colon\ \mu_t = \theta(L)^{-1}(1-L)^{-1}v_t \qquad (b4)$$

$$Seasonal\ :\ s_t = \delta' \theta(L)^{-1} d_t \qquad (b5)$$

$$Cycle\ :\ (y_t - \mu_t - s_t) = \theta(L)^{-1} e_t \qquad (b6)$$

Therefore, this allows the separate analysis of the non-stationary component μ_t and the stationary component $(y_t - \mu_t)$. The overall volatility of the series are governed by the two variances. $h = (h_v, h_e)$ along with the autoregressive parameters. The observed volatility are produced by the errors e_t, v_t (which are assumed to be iid normal).

The inverted lag operator has the representation:

$$\theta(L)^{-1} = \sum_{i=0}^{\infty} \gamma_i L^i \qquad (b7)$$

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

$$Var(\Delta\mu_t\ ) = \left(\sum_{j=0}^{\infty} \gamma_j^2\right) h_v \qquad (b8)$$

$$Var(y_t - \mu_t\ - s_t) = \left(\sum_{j=0}^{\infty} \gamma_j^2\right) h_e \qquad (b9)$$

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

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, since 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:

$$Var(\Delta\mu_t):\ volatility\ in\ mean$$

$$Var(y_t - \mu_t - s_t):\ volatility\ in\ cycle$$

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

$$lnh_{v,t} = \ln(h_v) + \lambda_v{}'\, z_t \qquad (b10)$$

$$lnh_{e,t} = \ln(h_e) + \lambda_e{}'\, z_t \qquad (b11)$$

Where z_t is a vector of variables as outlined in the main text in Section 3.1.

The two measures of volatility at a particular time then become:

$$Var(\Delta\mu_t) = \left(\sum_{j=0}^{\infty} \gamma_j^2\right) h_{v,t} \qquad (b12)$$

$$Var(y_t - \mu_t - s_t\ ) = \left(\sum_{j=0}^{\infty} \gamma_j^2\right) h_{e,t} \qquad (b13)$$

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

Restrictions and Identification

In the framework outlined above, equations $b12$ and $b13$ imply that the underlying volatility is governed by :

$$h_{v,t} = h_v \exp(\lambda_v{}'\, z_t) \qquad (b14)$$

$$h_{e,t} = h_e \exp(\lambda_e{}'\, z_t) \qquad (b15)$$

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 $\lambda_v\ or\ \lambda_e$ 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 where 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. In this work we avoid this problem by assuming $\lambda_v = \lambda_e = \lambda$. This implies that the long run and short run variances are proportional, but these variances can vary across in t. Since the values of h_v and h_e

will not be close to zero simultaneously (since the all the series have variation) the standard errors in the lambda coefficients will be smaller. This is obviously at a cost. If the shocks to volatility (z_t) impacted differently on the long and short run components, 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.

B2 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 and Ω. Therefore, the likelihood function can be denoted as $f(Y|\Omega,\mathrm{X})$. For prior distributions on Ω, $f(\Omega)$, the posterior distribution is denoted as $f(\Omega|\mathrm{Y},\mathrm{X})$ and obeys:

$$f(\Omega|\mathrm{Y},\mathrm{X}) \propto f(Y|\Omega,\mathrm{X})f(\Omega) \qquad (b16)$$

Where ∝ denotes proportionality. For the random parameter models, the parameters of interest are:

$$\Omega_* = \left(\{\theta_j\},\lambda_v,\lambda_e,h_v,h_e\right) \qquad (b17)$$

Normal priors are adopted for the parameters $\{\theta_j\},\lambda_v,\lambda_e$ where the mean is zero, with a large variance so as to reflect diffuse prior knowledge.[17] For the parameters h_v and h_e inverse gamma priors can be used, as is standard in Bayesian analysis.

For any values of $\Omega = (\lambda_v,\lambda_e,h_v,h_e)$ the Kalman Filter can produce optimal estimates of $\{\theta_j\}$, and standard errors for these parameters, along with the value of the likelihood function. Thus, in effect $\{\theta_j\}$ are ignored in the estimation of Ω since they are viewed as latent variables that are generated for any given values of Ω but are not required for the likelihood function. Estimation of the posterior distributions are then obtained using a random walk Metropolis-Hastings algorithm (see Koop, 2003, p97) to simulate the posterior distribution. The estimates of Ω ($\overline{\Omega}$) 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 $\{\theta_j\}$along with the standard errors are then obtained using the values $\overline{\Omega}$ within the Kalman Filter[18].

For the Panel Data a Bayesian approach to estimation is also used. In this case we use Gibbs Sampling [19]. The parameters are simply,

$$\Omega = (\{\beta_{oi}\},\{\beta_{1i}\},\lambda_v,\lambda,\Sigma) \qquad (b18)$$

Where Σ is the variance covariance matrix associated with the errors in equation (4) within the main text.

[17] Note that the priors for the autoregressive coefficients are set within the Kalman Filter.

[18] Note that these point estimates are therefore conditional on the plug in estimates and strictly speaking do not reflect the mean and variance of these parameters from a Bayesian perspective.

[19] A good coverage of Gibbs Sampling is given 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.