Modelling Regime-Dependent Agricultural Commodity Price Volatilities

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Abstract

In stark contrast to financial markets, relatively little attention has been given to modeling agricultural commodity price volatility. In recent years, numerous methodologies with various strengths have been proposed for modeling price volatility in financial markets. We propose using a mixture of normals with unique GARCH processes in each component for modeling agricultural commodity prices. While a normal mixture model is quite flexible and allows for time varying skewness and kurtosis, its biggest strength is that each component can be viewed as a different market regime and thus estimated parameters are more readily interpreted. We apply the proposed model to ten different agricultural commodity weekly cash prices. Both in-sample fit and out-of-sample forecasting tests confirm that the two-state NM-GARCH approach performs better than the traditional normal GARCH model. For each commodity, it is found that an expected negative price change corresponds to a higher volatility persistence, while an expected positive price change arises in conjunction with a greater responsiveness of volatility. A significant and state-dependent inverse leverage effect is detected only for corn in a highly volatile regime that occurs with a lower probability, indicating the volatility in this regime tends to increase more following a realized price rise than a realized price drop.

Key Words: GARCH, volatility, value at risk, normal mixture.
JEL *Classification*: G17, Q14

1 Introduction

Agricultural commodities are characterized by considerable price fluctuations that arise from several factors including unfavorable weather conditions, natural disasters (e.g. hurricanes), shifts in global demand and supply (due for example to agricultural policy changes) and exchange rate volatility. Agricultural commodity price volatility has been exceptionally high during the last decade (FAO and UNCTAD (2011)); food price volatility reached almost a 30-year high in December 2010 (Bellemare et al., 2013). Large and unpredictable price variations create a level of uncertainty which increases risks for producers, traders, consumers and governments. The substantial increase in the level and volatility of agricultural commodity prices during the 2006-2010 period renewed interest among policymakers, particularly in developing and emerging economies, as evidenced by government-managed price stabilization programs and multilateral efforts (among the Economic Community of West African States and the Association of Southeast Asian Nations) to institute strategic food reserves (Romero-Aguilar, 2015). Empirical studies by Mason and Myers (2013) and Bellemare et al. (2013) have not found such policies, especially price stabilization efforts, to be effective in mitigating impacts of price volatility on lower income consumers. Furthermore, many developing countries temporarily amended their trade policies in response to the rising and volatile prices. Exporting countries turned to export restrictions in the form of quotas, bans, and taxes (Bouët and Debucquet, 2012) while importing countries eliminated import tariffs (Demeke and Roux, 2014).

In developed countries, futures markets help food and agri-businesses mitigate the adverse effects of price fluctuations. For example, large grain elevators purchase grain from farmers on a forward contract basis and then hedge against the risk of falling prices by selling futures contracts for the same quantity of grain. However, managing price risk with futures contracts is more costly for producers and processors when prices are exceptionally volatile. This is because futures contracts are margined daily, leading to significant losses when margin calls are triggered by unexpected sharp price movements (Sam, 2009). For example, the dramatic surge in agricultural commodity prices in 2008 led to large margin calls for grain elevators, threatening their cash positions and causing some to increase their lines of credit substantially; some small and mid-size elevators simply filed for bankruptcy (Sam, 2009; Getu and Weersink, 2010).

In addition, volatile prices pose significant problems for market regulators and governments as they need greater human resource skills to manage markets in a volatile state. This is especially the case in underdeveloped countries where households may suffer severe food scarcity and food security problems. Barrett and Bellemare (2011) argue that welfare losses of price volatility are smaller for consumers than for producers because of the substitutability of food products and the imperfect correlation between their prices. That is, in the absence of a general increase in agricultural commodity prices, consumers can switch from a more expensive good to a relatively more affordable one. As for producers, large price uncertainty raises risks to investment and production decisions, particularly where the physical production cycle is long. It can spur less investment in crop inputs because producers must make irreversible investments decisions at the start of the growing season in a climate of highly uncertain output prices (Barrett and Bellemare (2011)). Volatility-induced reductions in crop investments lowers output, increases prices (Clapp (2009); Naylor and Falcon (2010)), and reduces welfare for net food buyers.

The challenge that high commodity price volatility brings highlights the need to better understand its causes, patterns, impacts and measures available to mitigate them. Modelling commodity price volatility helps to forecast the absolute magnitude, quantiles, and in fact, the entire distribution of price changes. Such forecasts are widely used in risk management, derivative pricing and hedging, portfolio selection, among other economic activities.

It is well known that agricultural prices exhibit time varying variance. Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models have been extensively used for modeling U.S. agricultural prices. Aradhyula and Holt (1988) show agricultural prices follow GARCH processes and that prices exhibit time-varying volatility. Han et al (1990) find that quartely aggregate U.S. farm price index exhibits conditional heterscedasticity. Using quarterly data, Saphores et al (2002) discover ARCH effects in Pacific northwest stumpage prices. Muthusamy et all (2008) model weekly wholesale fresh potato prices in Idaho using normally distributed GARCH errors. However, all these studies assume that errors are normally distributed. Although convenient and simple for estimation purposes, normal distributions do not allow skewness and leptokurtosis let alone time-varying upper moments. As an extension, Bollerslev (1987) proposed modelling innovations via a GARCH model with a Student's t-distribution and Fernández and Steel (1998) extended it further considering the skewed t-distribution.

A few recent studies have proposed using a mixture of two normal distributions to model volatility in equity markets. Among them, Haas et al. (2004) introduced the general symmetric Normal Mixture(NM) GARCH model, and Alexander and Lazar (2006) further investigated the property of NM-GARCH(1,1) model and provided empirical evidence that the generalized two-component NM-GARCH(1,1) models perform better than both symmetric and skewed Student's t-GARCH models for modelling exchange rates. A clear advantage of the NM-GARCH model over Students' t-GARCH models is the capability to model time-varying conditional skewness and kurtosis. Another advantage of NM-GARCH model is that it accounts for multiple states which enable economic interpretation. Haas et al. (2004), for example, pointed out that an NM-GARCH model accommodates the possibility of distinct types of responses to heterogeneous market shocks. Alexander and Lazar (2009) argued that a component with relative low variance could represent a "usual" state, which generally occurs, while a component with high variance could represent a "crash" state which rarely occurs.

An important empirical regularity of equity markets is the fact that volatility increases more after price declines than after price increases. Such an asymmetric return-volatility relationship is documented as a financial leverage effect in early influential studies (Black, 1976; Christie, 1982; Engle and Ng, 1993; Glosten et al., 1993). Engle and Ng (1993) introduced the Asymmetric GARCH (AGARCH) model allowing unequal effects of negative and positive shocks.

In commodity markets, contrary to equity markets, an "inverse leverage effect" may exist, i.e., a rise in the price level has stronger impact on the price volatility than a drop in the price. This is understandable, as increased prices of commodities generally bring panic and give rise to higher volatility. Previous studies, such as Geman and Shih (2009) and Chang (2012) found such an effect in energy markets. This effect has not been considered with respect to agricultural commodity markets.

In this manuscript we test whether NM-GARCH models are appropriate for modelling and forecasting agricultural commodity price volatility. In order to capture the possible state-specific asymmetric volatility responses to negative and positive shocks, as seen in equity markets, we followed Alexander and Lazar (2009) and also considered the NM-AGARCH model. For completeness we also consider the NM-symmetric-GARCH and FIGARCH models. Out-of-sample interval forecast validation, though pivotal in risk management and policy-making, has been rarely applied in past literature modelling volatility for agricultural commodity prices. In addition, we perform Value-at-Risk (VaR) validation tests. To the best of our knowledge, NM-GARCH models have not been used to consider volatility in agricultural commodity markets.

2 Literature Review

ARCH family, as a sophisticated group of time series volatility models, has been extensively surveyed by Bollerslev et al. (1992); Bera and Higgins (1993); Poon and Granger (2003). The seminal paper of Engle (1982) captured volatility clustering and heavy tails that are two stylized facts in financial time series data. Bollerslev (1986) introduced a generalized version of ARCH which reduces the number of parameters to be estimated by imposing autoregressive terms. Since then, numerous extensions have been made to GARCH models to capture asymmetry, long memory, structural breaks and regime switching behaviours in financial market data. Haas et al. (2004), among others, proposed extending the basic GARCH structure by assuming the conditional distribution of the error term as a mixture of normal distributions. NM-GARCH, though simple to estimate, is able to capture three regularities in financial asset returns: volatility clustering, heavy tails, and time-varying skewness.

Time-varying volatility is also a stylized fact observed in agricultural commodity price data. The empirical research on agricultural price volatility has focused on the dependence of price volatility across related markets (Apergis and Rezitis, 2003; Buguk et al., 2003; Rezitis and Stavropoulos, 2010; Serra et al., 2011; Serra and Gil, 2013; Serra, 2013) and determinants of price volatility (Shively, 1996; Hennessy and Wahl, 1996; Karali and Power, 2013). For example, using a multivariate GARCH model with exogenous variables incorporated in the conditional covariance model, Serra and Gil (2013) found U.S. corn price volatility could be explained by volatility clustering, the influence of biofuel prices, corn stocks and global economic conditions. Karali and Power (2013) explained price volatility in the U.S. commodity futures markets, using a spline-GARCH model of Engle and Rangel (2008) that produces estimates of low-frequency volatility. Estimates are then regressed against a series of macroeconomic variables. The study is based on 11 different daily futures prices observed from April 1990 to November 2009. The U.S. Treasury interest rate spread

(10-year to 2-year) is found to have negative impact on price volatility for corn, crude oil, heating oil and hopper, with the largest effect for crude oil. Working's theory of storage, whereby volatility is decreasing in inventories, is supported for corn, wheat, lean hogs, and crude oil.

The number of empirical tests of structural models in agricultural commodity prices is surprisingly limited. Hall et al. (1989) detected unconditional leptokurtic distribution in twenty daily futures price series and found support for the normal mixture distribution hypothesis relative to a stable Paretian distribution hypothesis by applying the stability-under-addition test. Yang and Brorsen (1992) were among the first to empirically test for a GARCH structure in agricultural commodity prices. They found that GARCH models with a conditional Student's t-distribution fit daily price change data better than a number of alternatives; however, both the Student's t distribution and the normal did not correctly specify the conditional distribution according to the Kolmogorov-Smirnov test. Jin and Frechette (2004) found fractionally integrated generalized autoregressive conditional heteroscedastic (FIGARCH) model performs significantly better than the basic GARCH(1,1) models in modelling volatility of 14 agricultural futures price series, confirming long-term memory of volatility. They explained many factors can lead to long-term dependence in agricultural futures price volatility, such as supply lags, inventory holding, business cycles, agricultural policies and heterogeneity among traders.

Previous research suggests the GARCH model with a conditional normal distribution or Student's t-distribution does not adequately model the agricultural commodity prices. Jin and Frechette (2004)'s finding support FIGARCH model over the basic GARCH(1,1) models in modelling volatility with long-term memory. However, as with other single-state models, FIGARCH model can not capture state-dependent volatility dynamics and is subject to the stringent assumption of constant skewness and kurtosis. Alternatively, the persistence in commodity price volatility can also be modelled by the GARCH part of the NM-GARCH model. In fact, the causes that lead to persistent price volatility as listed by Jin and Frechette (2004) also contribute to a multi-regime market and regime-dependent volatility dynamics. On the one hand, supply lags and business cycles may lead to incidences of different market states, on the other hand, agricultural policies, inventory holding and trade behaviours tend to be different under stable and turbulent price environments. Therefore it is interesting to access weather an NM-GARCH(1,1) model allowing for state-dependent volatility dynamics can adequately capture the relevant properties of agricultural commodity prices.

3 Model and Data

The innovation, denoted by the error term ε_t, is assumed to follow a mixture of k Gaussian distributions with distinct component mean μ_i and component variance σ^2_{it}. That is,

$$\varepsilon_t|\Omega_{t-1} \sim \mathrm{NM}(p_1, \ldots, p_k, \mu_1, \ldots, \mu_k, \sigma^2_{1t}, \ldots, \sigma^2_{kt}),$$

where Ω_t is the information set at time t, $p_i \in (0,1)$, $i = 1, \ldots, k$ are mixing weights, $\sum_{i=1}^{k} p_i = 1$ and $\sum_{i=1}^{k} p_i\mu_i = 0$. We consider two possibilities for the conditional variance of k components.

(i) NM(k)-GARCH(1,1):

$$\sigma^2_{it} = \omega_i + \alpha_i\varepsilon^2_{t-1} + \beta_i\sigma^2_{it-1} \qquad \text{for } i = 1, \ldots, k, \tag{1}$$

where α_i is defined as the volatility reaction parameter, indicating the effect of market shocks on volatility, and β_i is defined as the volatility persistence parameter, referring to the extent of inertia in volatility. The NM(k)-symmetric-GARCH(1,1) models assumes $\mu_1 = ... = \mu_k = 0$.

(ii) NM(k)-AGARCH(1,1):

$$\sigma_{it}^2 = \omega_i + \alpha_i \left(\varepsilon_{t-1} - \lambda_i\right)^2 + \beta_i \sigma_{it-1}^2 \qquad \text{for } i = 1, \ldots, k, \tag{2}$$

where λ_i is the leverage parameter.

Both the NM-GARCH and NM-AGARCH models allow for different non-zero component means, thus capturing overall unconditional or persistent asymmetry in the state-dependent data. As the NM-AGARCH model includes a leverage parameter λ_i, it is able to capture state-dependent dynamic asymmetry in the data. For example, a negative λ_i indicates the conditional variance in this regime tends to be higher following a price increase than a price decrease. In commodity markets, an "inverse leverage effect" or a negative value of the leverage parameter is expected because a rise in commodity prices generally brings panic and gives rise to higher volatility.

We analyze weekly cash prices of three grains, four meat and three dairy products obtained from the Livestock Marketing Information Center (LMIC). Because of data availability, the time periods across commodities are different. Specifically, we consider the following agricultural commodities (the data is illustrated in Figures 1,2, and 3):

(i) grains: corn, sorghum and wheat weekly cash price series for the January 1988 to July 2013 period (1332 observations);

(ii) meat: beef weekly cash prices for the July 1999 to July 2013 period (758 observations), pork weekly cash prices for the January 1988 to April 2013 period (795 observations), broiler and turkey weekly cash prices for the January 1992 to December 2012 period (991 observations).

(iii) dairy products: cheddar, butter and nonfat dry milk (NFDM) for the September 1998 to February 2013 period (753 observations).

For each commodity, we fit the continuously compounded percentage changes of prices, $r_t = 100(\log P_t - \log P_{t-1})$ with an autoregressive-moving-average (ARMA(u,v)) model.

$$r_t = c + \varepsilon_t + \sum_{i=1}^{u} a_i r_{t-i} + \sum_{j=1}^{v} b_j \varepsilon_{t-j}$$

An Akaike information criterion with a correction for finite sample sizes (AICc) is used to select the appropriate values of u and v. Then we subtract the means of each series and perform estimation of the NM-GARCH models by the expectation-maximization (EM) algorithm of Dempster et al. (1977).

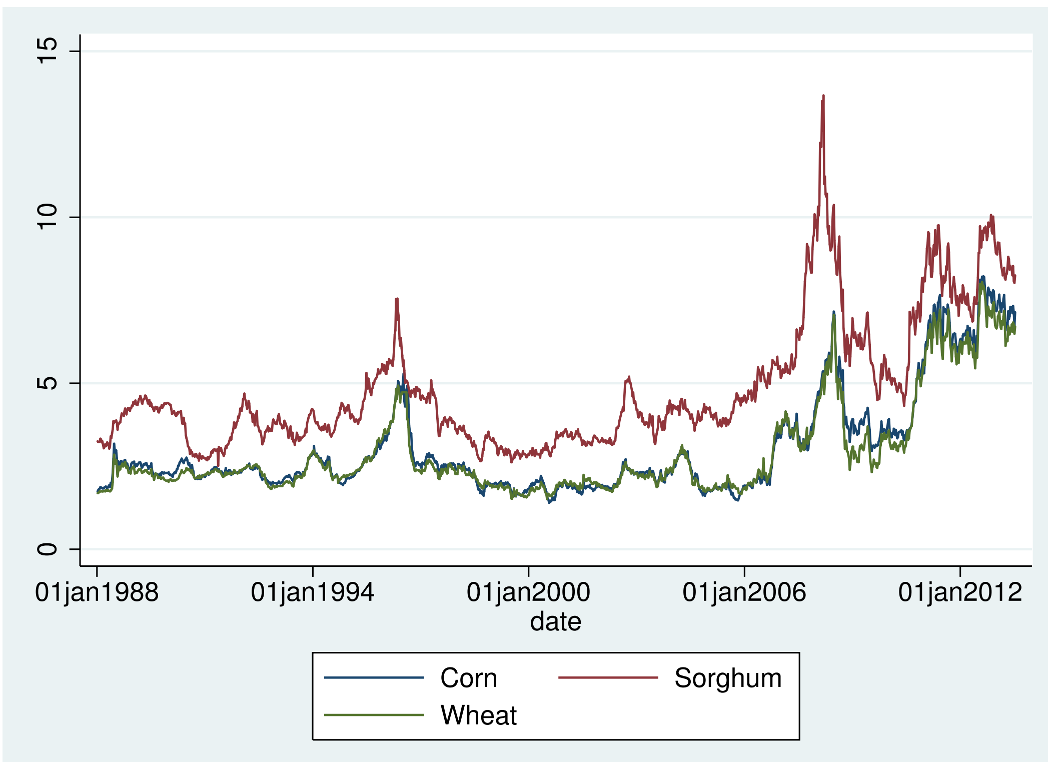

Figure 1: Price levels of grains

4 Estimation Results and Implications

The GARCH(1,1), the NM(2)-GARCH(1,1), and the NM(2)-GJR-GARCH(1,1) models are estimated for each of the food price series. The estimation results are given in

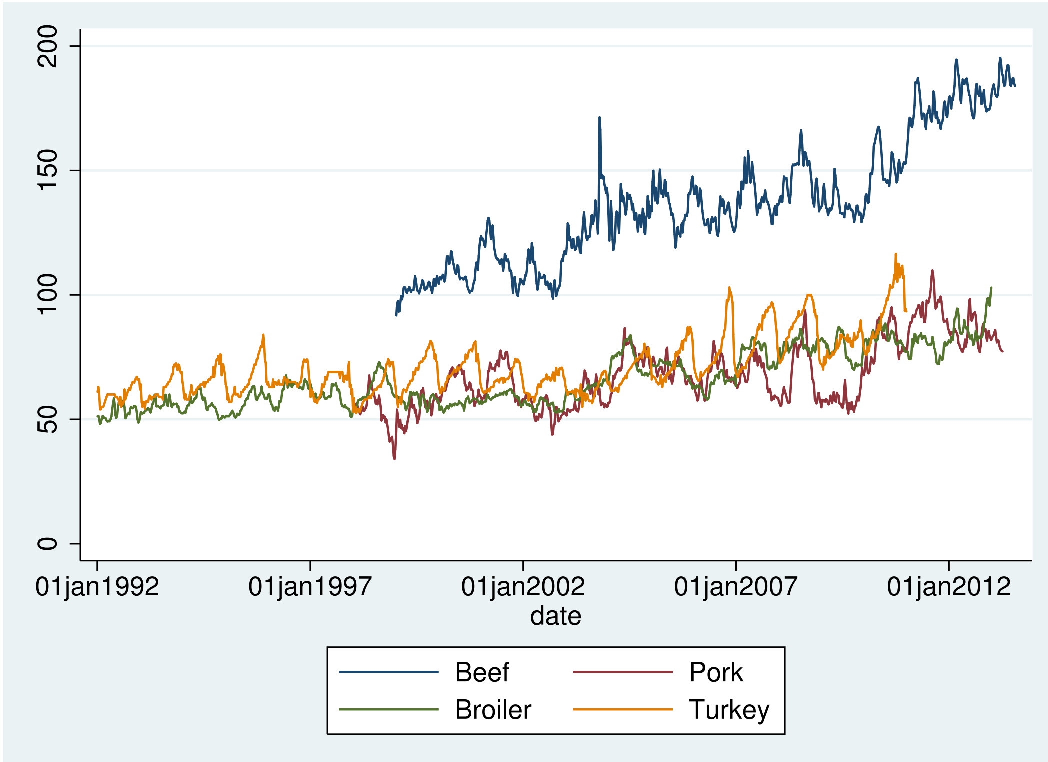

Figure 2: Price levels of meat

Tables 1–3.

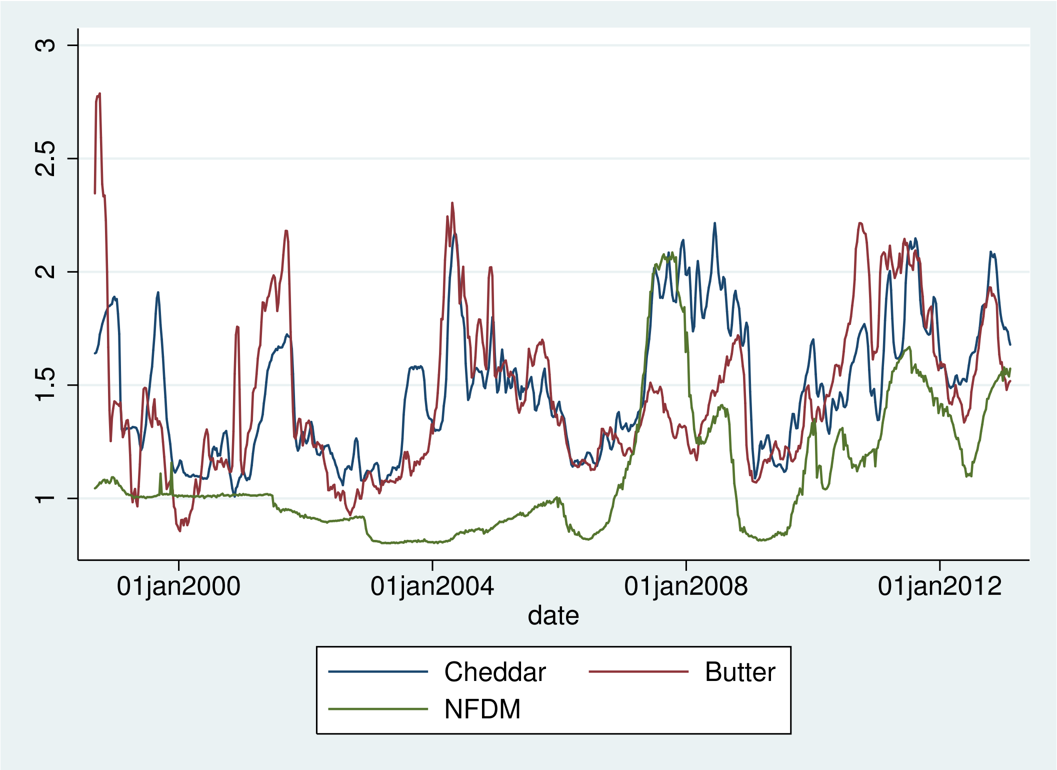

Figure 3: Price levels of dairy products

Table 1: Estimation results for grains

	p_1	μ_1	ω_1	d	α_1	β_1	λ_1	μ_2	ω_2	α_2	β_2	λ_2
Corn												
GARCH			0.5526***		0.2007***	0.7828***						
			(0.1660)		(0.0275)	(0.0258)						
FIGARCH			0.5879***	0.7113***	0.2100**	0.6715***						
			(0.2201)	(0.1510)	(0.0872)	(0.0991)						
NM-symmetric	0.3351***		0.7173***		0.5334	0.7381***				1.0155***	0.0783**	0.7067***
	(0.0520)		(0.8341)		(0.1619)	(0.0601)				(0.3224)	(0.0304)	(0.0569)
NM-GARCH	0.3423***	-0.4118*	1.5749***		0.4443***	0.7297***			0.2143	0.5439	0.0419***	0.8452***
	(0.0495)	(0.2371)	(0.5962)		(0.1025)	(0.0379)				(0.3630)	(0.0152)	(0.0669)
NM-AGARCH	0.3326***	-0.3904***	0.7551		0.6122***	0.7004***	-0.3025	0.1946	0.7407***	0.1144***	0.4679***	0.5038
	(0.0127)	(0.1332)	(0.5811)		(0.1311)	(0.0554)	(0.2866)		(3.2570)	(0.0295)	(0.1213)	(0.4273)
Sorghum												
GARCH			0.3687***		0.1451***	0.8485***						
			(0.1174)		(0.0187)	(0.0170)						
FIGARCH			0.5958**	0.5393***	0.3930**	0.7228***						
			(0.2329)	(0.1162)	(0.0813)	(0.0665)						
NM-symmetric	0.3469		0.7839**		0.2961**	0.8441***				0.4373*	0.1013***	0.7193***
	(0.2172)		(0.3229)		(0.1429)	(0.0203)				(0.2658)	(0.0217)	(0.1192)
NM-GARCH	0.3532***	-0.0203	1.7840		0.3447***	0.7709***			0.0111	0.4381	0.1049***	0.7178***
	(0.1073)	(0.1796)	(1.1431)		(0.0492)	(0.0559)				(0.2844)	(0.0262)	(0.1177)
NM-AGARCH	0.2999***	-0.0790	16.1896*		0.4180***	0.3173	-0.1805	0.0338	0.2582***	0.122***	0.7507***	-0.3571
	(0.0126)	(0.1429)	(9.1500)		(0.1125)	(0.2870)	(0.7879)		(0.0828)	(0.0190)	(0.0324)	(0.2741)
Wheat												
GARCH			1.1638***		0.142***	0.7769***						
			(0.3417)		(0.0290)	(0.0457)						
FIGARCH			2.7298**	0.2788***	0.1280	0.2740						
			(1.1617)	(0.0582)	(0.2224)	(0.2421)						
NM-symmetric	0.1475		9.2233		0.9062	0.4402*				0.3549	0.0531***	0.8838***

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Table 1 – continued from previous page

	p_1	μ_1	ω_1	d	α_1	β_1	λ_1	μ_2	ω_2	α_2	β_2	λ_2
	(0.1104)		(7.9163)		(0.7815)	(0.2598)				(0.3331)	(0.0143)	(0.0665)
NM-GARCH	0.1243***	0.3398	8.2884*		0.6062**	0.5323**			-0.0483	0.3618	0.0743	0.8601***
	(0.0481)	(0.5603)	(4.5265)		(0.3018)	(0.2241)				(0.4982)	(0.0460)	(0.1170)
NM-AGARCH	0.1392***	0.3360	6.7075		0.5394***	0.3158	-3.5595***	-0.0543	0.2061**	0.1056***	0.8509***	0.0489
	(0.0095)	(0.2889)	(5.0571)		(0.1960)	(0.2382)	(1.0562)		(0.1046)	(0.0287)	(0.0376)	(0.4766)

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Numbers in parentheses represent standard errors

Table 2: Estimation results for meat

	p_1	μ_1	ω_1	d	α_1	β_1	λ_1	μ_2	ω_2	α_2	β_2	λ_2
Beef												
GARCH			0.3252**		0.1220***	0.8216***						
			(0.1417)		(0.0389)	(0.0547)						
FIGARCH			0.2810	0.3636***	0.4349**	0.6588***						
			(0.1449)	(0.1072)	(0.1147)	(0.1062)						
NM-symmetric	0.1783***		0.3033		0.3997***	0.8228***				0.9315**	0.1427**	0.5599***
	(0.0549)		(0.5600)		(0.1143)	(0.0799)				(0.4185)	(0.0567)	(0.1561)
NM-GARCH	0.1707***	1.0806**	0.3440		0.4878	0.7562***			-0.2225	1.1974**	0.1626***	0.4772***
	(0.0183)	(0.4687)	(0.3834)		(0.3125)	(0.0778)				(0.5685)	(0.0615)	(0.1772)
NM-AGARCH	0.1774***	0.9780***	0.0087		0.5200***	0.7632***	-0.3584	-0.2109	1.4690***	0.1296***	0.4180***	0.4343
	(0.0071)	(0.1680)	(0.0863)		(0.0531)	(0.0164)	(0.2976)		(0.0790)	(0.0253)	(0.0667)	(0.2805)
Pork												
GARCH			2.9963***		0.2837***	0.4637***						
			(0.7565)		(0.0578)	(0.0930)						
FIGARCH			1.9946*	0.2758***	0.0770	0.2212						
			(1.1435)	(0.0821)	(0.2737)	(0.3066)						
NM-symmetric	0.4508**		4.2483***		0.4014**	0.4927***				2.3825*	0.1621*	0.3671***
	(0.1828)		(1.4871)		(0.1665)	(0.1463)				(1.3608)	(0.0840)	(0.1162)
NM-GARCH	0.4512**	0.3328	3.7113**		0.4357**	0.5108***			-0.2736	2.5405*	0.1558*	0.3229***
	(0.2033)	(0.2539)	(1.4452)		(0.1914)	(0.1376)				(1.3670)	(0.0870)	(0.0614)
NM-AGARCH	0.4499***	0.3509***	3.7773***		0.4158***	0.5119***	-0.0095	-0.2870	3.2091***	0.1652***	0.2025	-0.7073*
	(0.0177)	(0.1192)	(1.4381)		(0.1550)	(0.0235)	(0.2652)		(1.0481)	(0.0273)	(0.2229)	(0.3905)
Broiler												
GARCH			1.9922**		0.2984***	0.2071***						
			(0.2905)		(0.0569)	(0.0870)						
FIGARCH			2.0547***	0.0301	0.3003	0.1437						
			(0.4688)	(0.0391)	(0.1839)	(0.1682)						
NM-symmetric	0.4202***		0.2266		0.0257	0.5335*				3.2236***	0.4524***	0.2054*

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Table 2 – continued from previous page

	p_1	μ_1	ω_1	d	α_1	β_1	λ_1	μ_2	ω_2	α_2	β_2	λ_2
	(0.0452)		(0.2270)		(0.0163)	(0.2750)				(0.6722)	(0.1233)	(0.1202)
NM-GARCH	0.4041***	0.0183	0.1444		0.0507*	0.5327*			-0.0124	3.1058***	0.4272***	0.2242*
	(0.0475)	(0.0577)	(0.1498)		(0.0270)	(0.2718)				(0.6674)	(0.1195)	(0.1257)
NM-AGARCH	0.3988***	0.0237	0.1551***		0.0543***	0.4925***	0.2367	-0.0157	2.9604***	0.4143***	0.1223*	-1.4252
	(0.0148)	(0.0344)	(0.0538)		(0.0134)	(0.1079)	(0.2190)		(0.6278)	(0.1039)	(1.9485)	(0.1541)
Turkey												
GARCH			1.5422***		0.3287***	0.5258***						
			(0.3017)		(0.0544)	(0.0596)						
FIGARCH			1.0697**	1***	0	0.5389**						
			(0.4822)	(0.2502)	(0.1198)	(0.2262)						
NM-symmetric	0.366***		3.2948**		0.5973***	0.5744***				1.0719*	0.1157***	0.1480
	(0.0840)		(1.3679)		(0.2001)	(0.1096)				(0.5655)	(0.0321)	(0.1957)
NM-GARCH	0.3595	-0.7788	4.0189*		0.3486	0.6152**			0.4371	0.8666	0.0821	0.2572
	(0.3491)	(1.5344)	(2.0595)		(0.3161)	(0.3118)				(1.4003)	(0.0506)	(0.4985)
NM-AGARCH	0.3658***	-0.7251***	4.3806***		0.5899***	0.4299***	1.8643***	0.4182	0.8095***	0.1240***	0.1269***	1.3961***
	(0.0148)	(0.0863)	(1.2738)		(0.1939)	(0.1022)	(0.4907)		(0.1202)	(0.0221)	(0.0722)	(0.2712)

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Numbers in parentheses represent standard errors

Table 3: Estimation results for dairy products

		p_1	μ_1	ω_1	d	α_1	β_1	λ_1	μ_2	ω_2	α_2	β_2	λ_2
Cheddar													
	GARCH			1.4877***		0.8093***	0.2778						
				(0.3903)		(0.0966)	(0.0895)						
	FIGARCH			0.563***	0.6918***	0	0.2997						
				(0.2001)	(0.2362)	(0.1861)	(0.2770)						
	NM-symmetric	0.4331***		1.8884**		0.9985***	0.266***				1.0263***	0.4914***	0.0319
		(0.0906)		(0.7560)		(0.2024)	(0.1019)				(0.3298)	(0.1069)	(0.0502)
	NM-GARCH	0.4375***	-0.4591***	2.0721***		0.9989***	0.2416**			0.3571	0.9404**	0.4659***	0.0221
		(0.0618)	(0.0899)	(0.7658)		(0.2024)	(0.0980)				(0.4447)	(0.0965)	(0.0458)
	NM-AGARCH	0.3898***	-1.0793***	0.3168		0.5963***	0.2685***	-1.8796***	0.6895	0.4614***	0.9265***	0.0569**	0.7660***
		(0.0157)	(0.0848)	(0.1996)		(0.0883)	(0.0645)	(0.1506)		(0.0995)	(0.0774)	(0.0284)	(0.0792)
Butter													
	GARCH			1.4275***		0.4227***	0.5066***						
				(0.3614)		(0.0837)	(0.0746)						
	FIGARCH			0.667*	0.3395***	0.4675**	0.5908***						
				(0.3778)	(0.0940)	(0.1498)	(0.1714)						
	NM-symmetric	0.2202***		2.3676		0.9904***	0.6300***				1.9751***	0.2057***	0.1986
		(0.0766)		(1.7824)		(0.3807)	(0.0901)				(0.5914)	(0.0658)	(0.1396)
	NM-GARCH	0.2285**	-0.5347	2.4461		0.9952**	0.6288***			0.1583	2.0692***	0.1825**	0.1896
		(0.1082)	(0.3473)	(2.7269)		(0.4083)	(0.0905)				(0.7016)	(0.0723)	(0.1583)
	NM-AGARCH	0.2300***	-0.3720	1.8600*		0.9510***	0.6580***	0.3910	0.1111	2.0600***	0.1680***	0.1920*	-0.0001
		(0.0154)	(0.2270)	(1.0100)		(0.3200)	(0.0730)	(0.4610)		(0.4100)	(0.0401)	(0.1130)	(0.0296)
NFDM													
	GARCH			0.1692***		0.295***	0.7367***						
				(0.0225)		(0.0446)	(0.0235)						
	FIGARCH			0.1786***	0.7536***	0.2665**	0.6935***						
				(0.0390)	(0.1687)	(0.1158)	(0.0811)						

Continued on next page

Table 3 – continued from previous page

	p_1	μ_1	ω_1	d	α_1	β_1	λ_1	μ_2	ω_2	α_2	β_2	λ_2
NM-symmetric	0.0713***		2.8513		0.6241	0.7773***				0.0294***	0.3303***	0.5455***
	(0.0169)		(3.1251)		(0.4381)	(0.1537)				(0.0081)	(0.0512)	(0.0436)
NM-GARCH	0.0638***	-0.9065**	1.4289		0.5004	0.8558***			0.0618	0.0313***	0.3107***	0.557***
	(0.0146)	(0.3644)	(0.8850)		(0.3522)	(0.0772)				(0.0082)	(0.0467)	(0.0445)
NM-AGARCH	0.0653***	-0.8862***	10.1659		0.6857	0.0071	4.4024	0.0619	0.0335***	0.3299***	0.5443***	-0.0546
	(0.0089)	(0.3151)	(20.43)		(0.5264)	(0.6265)	(3.1788)		(0.0077)	(0.0457)	(0.0394)	(0.0478)

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Numbers in parentheses represent standard errors

Estimation results are presented in Tables 1, 2 and 3, respectively for grains, meat, and dairy products. For most commodities, the NM-GARCH model captures a lower-volatility component that occurs with a high probability (the usual regime) and a high-volatility component that occurs with a low probability (the unusual regime). Among them, NFDM has the most unbalanced occurrence of the two market regimes, with the unusual market regime occurring 10% of the time. For broiler and cheddar, however, the two market regime occurred somewhat evenly over time, indicating a two-regime model may be inappropriate for these. A noticeable result regarding the NM-GARCH models is that similar to Haas et al. (2004), Alexander and Lazar (2006, 2009), and Bauwens et al. (2007), the component that has small mixing weights may have unstable volatility dynamics in the sense that $\alpha_i + \beta_i > 1$.

The usual mean component is lowest and negative in the beef (-.53% per week) but the unconditional volatility is also low: at 1.4%, it is the lowest in the usual regime. On the other hand, corn price has the most expected increase (.34% per week) and the second highest volatility of the ten markets (around 4%, second to Sorghum (4.5%)). In the usual regime the wheat series exhibits the least reactive and most persistent volatility.

In the unusual market regime, NFDM has the highest unconditional volatility (over 10%). Most series, wheat and NFDM in particular, are highly reactive to market shocks in the unusual regime, yet because the persistence are all low, the effect of a shock decays soon.

There is a clear-cut relationship between the component mean (μ_i) and the component volatility dynamics (reflected by α_i and β_i). For each commodity, expected negative price change corresponds to a greater volatility persistence parameter β_i, indicating volatility tends to be more persistent when shocks are negative.[1] On the other hand, expected positive price changes arise in conjunction with a higher volatil-

[1] A sole exception is pork, the component means and mixing weights of which are not significantly different from 0.

ity reaction parameter (α_i), suggesting volatility is more reactive to price rises than price drops. This is just the opposite of the case in the equity markets, where, for example, Haas et al. (2004) found volatility is more stable when shocks are positive, while more responsive to negative shocks. Note that the state-dependent volatility dynamics are not detectable in previous research on agricultural commodity prices as single-state GARCH models only capture an average of these effects if multiple states exist.

The NM-AGARCH model is found to suffer the problem of over parameterization for some commodities, on the grounds that it gives estimates that reach the boundary values in numerical optimization. For the rest of commodities, it gives similar results to the NM-GARCH model. The asymmetric parameters (λ_i) in the NM-AGARCH for most commodities are insignificant except on occasions when component means are negative. For example, corn has a significant inverse leverage effect in the unusual regime where the price is expected to drop. Beef, on the other hand, has a significant leverage effect during the usual regime where price falls are expected. A possible explanation is that there are more beef producers who have long interest in their products than physical hedgers, therefore in anticipation of falling prices a realized price drop leads to panic and pushes implied volatility up. The fact that inverse leverage effect is state-dependent (only significant in a regime where negative shock are expected) also permits more refined risk management practice and market regulation in agricultural markets than those based on single-state GARCH models.

4.1 Diagnostic Checks and Forecasting Performance

To assess the in-sample fit provided by the three models, we have applied several model selection criteria. First, we test the normality of the standardized residuals. As standardized residuals of GARCH-type models may not be identically distributed, we proceed with a transformation pioneered by Berkowitz (2001) and extended to

NM-GARCH model testing by Haas et al. (2004) and Alexander and Lazar (2009). Specifically,

$$z_t = \Phi^{-1}\left(\hat{F}(\varepsilon_t|\Omega_{t-1})\right), \tag{3}$$

where Φ^{-1} is the inverse function of standard normal cumulative distribution function, and $\hat{F}(\cdot)$ is the conditional distribution function of the error term ε_t. If the model correctly specifies the underlying data generating process (DGP), then the transformed residuals z_t's should be identically independently distributed standard normal. As noted by Berkowitz (2001), the transformed residuals would preserve inaccuracies in the specified density, therefore Equation (3) can be used to check correct specification of moment features such as skewness and kurtosis. Specifically, let T be the sample size, g_1 denotes the sample skewness of z_t and g_2 the sample kurtosis, if z_t's are normally distributed, then $m_1 = Tg_1^2/6 \overset{asy}{\sim} \chi^2(1)$ and $m_2 = T(g_2-3)^2/24 \overset{asy}{\sim} \chi^2(1)$. In addition, the following Jarque and Bera (1987) (JB) test is implemented to check the normality of the transformed series z_t.

$$JB = m_1 + m_2 \overset{asy}{\sim} \chi^2(2).$$

Table 4 summarizes the results for the in-sample fit. Results show that the normal GARCH model fails the skewness and/or kurtosis tests for all commodities except for pork. The JB normality test results further show that transformed residuals of the normal GARCH models for all price series except pork exhibit strong deviations from normality. However even for pork, NM-type models have smaller JB-statistics indicating a better fit. The performance of the NM-GARCH model and the NM-AGARCH models are comparable and consistently well for most commodities, indicating time-varying conditional skewness and kurtosis specification exists and requires a model that can accommodate such.

Table 4: In-sample Fit Test

	Skewness	Kurtosis	JB
Corn			
GARCH	-0.13*	0.95***	53.7***
FIGARCH	-0.13*	0.97***	56.1***
MN-symmetric	-0.1	-0.13	3.2
MN-GARCH	-0.01	-0.1	0.5
MN-AGARCH	-0.02	-0.09	0.5
Sorghum			
GARCH	-0.04	3.58***	709.9***
FIGARCH	-0.03	3.03***	509.7***
MN-symmetric	-0.01	0.46***	11.6***
MN-GARCH	-0.05	0.69***	27.1***
MN-AGARCH	-0.01	0.28**	4.5
Wheat			
GARCH	-0.02	2.97***	490.7***
FIGARCH	-0.01	3.35***	622.2***
MN-symmetric	0.04	0.13	1.2
MN-GARCH	0.004	0.19	1.9
MN-AGARCH	0.05	0.09	0.9
Beef			
GARCH	0.57***	1.06***	76.6***
FIGARCH	0.7***	1.01***	93.8***
MN-symmetric	0.32***	-0.21	14***
MN$_GARCH$	0.17*	-0.2	4.9*
MN-AGARCH	0.18**	-0.28	6.6***
Pork			
GARCH	0.07	0.44**	7.2***
FIGARCH	-0.08	0.25	2.9
MN-symmetric	0.07	-0.13	1.2
MN-GARCH	-0.02	-0.13	0.6
MN-AGARCH	-0.04	-0.11	0.6
Broiler			
GARCH	0.11	1.54***	111.2***
FIGARCH	0.05	1.34***	82.8***
MN-symmetric	0.03	0.03	0.2
MN-GARCH	0.05	0.05	0.6
MN-AGARCH	0.02	0.03	0.1
Turkey			
GARCH	-0.75***	4.18***	813.7***
FIGARCH	-0.68***	4.62***	959.5***
MN-symmetric	-0.42***	0.47***	38.4***
MN-GARCH	-0.06	0.19	1.9
MN-AGARCH	-0.05	0.14	1.1
Cheddar			
GARCH	-0.38***	0.84***	40.1***
FIGARCH	-0.33***	2.16***	160.3***
MN-symmetric	-0.29***	-0.01	10.6***
MN-GARCH	-0.07	-0.08	0.8
MN-AGARCH	-0.02	0.24	1.8
Butter			

Continued on next page

Table 4 – continued from previous page

	Skewness	Kurtosis	JB
GARCH	-0.07	2.46***	190.9***
FIGARCH	-0.06	2.38***	178.6***
MN-symmetric	-0.1	-0.05	1.3
MN-GARCH	0.32***	1.74***	108.4***
MN-AGARCH	0.03	-0.07	0.3
NFDM			
GARCH	-1.02***	11.72***	4,438***
FIGARCH	-1.02***	11.47***	4,257***
MN-symmetric	-0.22	0.23	7.6**
MN-GARCH	-0.01	0.2	1.3
MN-AGARCH	-0.04	0.19	1.3

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

As volatility models are widely employed in risk management, we also assess the accuracy of Value-at-Risk (VaR) predictions. VaR is defined as the conditional τ-quantile, $\Pr\left(y_t \leq \mathrm{VaR}_t(\tau)|\Omega_{t-1}\right) = \tau$, where τ is also defined as shortfall rate or failure rate, representing the probability that the loss exceeds the VaR threshold. It is widely used to measure the downside risk on a specific portfolio of financial assets. Although many VaR backtesting criteria having been proposed, no consensus has been reached about the best method. Thus we employ two VaR backtesting methods in this manuscript.

For out-of-sample VaR, we follow Alexander and Lazar (2009) and use the conditional coverage test introduced by Christoffersen (1998). The hypotheses are that the realization of the variable lies outside the $(1-\tau)\times 100\%$ forecast interval $\tau \times 100\%$ of the time, and such violations should also be independent across time. In the case of VaR, the intervals are one-sided from the threshold value $\mathrm{VaR}_t(\tau)$ to infinity.

Define $I_t\left\{r_t < \mathrm{VaR}_t|\Omega_{t-1}\right\}, t = 1, \ldots, T$ as the indicator sequence. A conditional coverage test is a joint test of unconditional coverage test $(E\left(I_t\right) = \tau)$ and independent test $(\Pr\left(I_t = 1|I_{t-1} = 0\right) = \Pr\left(I_t = 1|I_{t-1} = 1\right))$. Unexpected or prolonged agricultural price spikes typically raise alerts to policy makers and upstream food processors that rely on that commodity as inputs. For example, livestock enterprises are interested to know the highest levels feed prices could rise. Therefore, we also assess the accuracy of the upper quantile prediction of the competitive models. The upper tail risk also represents VaR for traders in a short selling position, see Giot and Laurent (2003) for an applied example.[2]

Table 5 report the Christoffersen conditional coverage likelihood ratio test statistics (LR_{CC}). It is shown that the normal GARCH model fails all VaR(5%) tests whereas the NM-GARCH model passes all the VaR tests and the NM-AGARCH model only fails the test for beef, suggesting that the NM-GARCH and the NM-AGARCH models are suitable for VaR calculation but the normal GARCH model is not. Test results for implied 95% quantile forecasts also confirm the conclusion that the normal GARCH model gives the worst fit. It only correctly predicts the in-sample 95% quantile for beef but fails the interval tests for all other commodities.[3] NM-GARCH and NM-AGARCH models only fail one upper-tail test respectively.

[2]Securities or other financial instruments not currently owned are short-sold by traders with the intention of subsequently repurchasing them at a lower price. The short seller incurs a loss when price rises to a higher prices than the proceeds of initial sale.

[3]A VaR(1%) test and 99% quantile test were also undertaken; they yield similar conclusions as the normal GARCH forecast is overly cautious. For most commodities there is no violation in the sample and thus the Christoffersen test statistics are not computable.

Table 5: Out-of-sample VaR test results

	VaR with 95% confidence					VaR with 99% confidence				
	GARCH	FI-GARCH	NM-symmetric	NM-GARCH	NM-AGARCH	GARCH	FI-GARCH	NM-GARCH	NM-symmetric	NM-AGARCH
LR test										
Corn	388.95	29.72***	6.19**	1.59	1.59	621.28	108.03***	2.73	0.22	0.22
Sorghum	Inf	29.2***	0.19	1.69	2.46	Inf	80.88***	0.83	0.83	4.05
Wheat	130.77***	40.9***	0.37	1.46	0.57	145.75***	69.13***	0.44	0.22	0.22
Beef	20.09***	32.2***	0.94	4.75*	1.11	3.61	31.55***	3.15	0.29	1.19
Pork	4.08	14.0***	2.06	0.01	0.03	15.27***	32.62***	1.67	0.23	1.67
Broiler	58.87***	17.7***	8.3**	10.91***	7.40**	92.17***	221.37***	0.15	0.15	0.24
Turkey	11.27*	8.50**	3.23	1.43	3.00	3.59	72.87***	2.24	0.66	0.66
Cheddar	69.14**	7.70**	27.29***	27.07***	23.32***	42.89***	150.86***	5.50	5.50*	5.50*
Butter	20.34***	11.17***	4.57	7.18**	4.69*	44.42***	54.61***	11.95	4.29	6.52**
NFDM	161.59***	0.01	17.87***	18.27***	18.11***	242.65***	72.35***	11.83	9.86***	8.14**
GMM test										
Corn	9,124***	24.27***	40.08***	10.86***	12.08***	96,900***	1,634***	2.25	0.03	6.75**
Sorghum	13,652***	26.15***	4.29	8.63**	7.38**	204,513***	592.4***	2.16	4.99*	4.57
Wheat	1,321***	39.30***	0.96	0.29	0.62	4156***	196.3***	0.03	0.46	6.75**
Beef	45.66***	27.64***	2.44	1.57	0.07	9.95***	170.0***	4.25	0.32	0.83
Pork	1.65	12.55***	0.7	0.21	0.04	41.19***	124.2***	0.42	1.09	4.54
Broiler	103.8***	129.9***	2.3	0.96	1.8	627.6***	14,748***	2.38	0.78	1.37
Turkey	7.50**	6.19**	0.4	1.41	0.36	1.70	539.2***	2.85	0.53	0.53
Cheddar	247.4***	8.38**	155.8***	51.32***	27.16***	1,099***	10,330***	0.56	9.95***	9.95***
Butter	21.45***	6.08**	1.05	1.19	1.14	211.7***	324.2***	0.56	0.56	1.36
NFDM	3,926***	0.64	15.76***	50.08***	32.12***	49,495***	860.3***	31.61***	32.06***	20.05***

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Next, we use a generalized method of moments (GMM) based approach proposed by Dumitrescu et al. (2013) to test out-of-sample forecasting performance of the models with respect to VaR(1%) (in accordance with Basel II requirement) as well as 99% quantile prediction. The GMM based approach test Christoffersen's three validity hypotheses independently. It has better power and small-sample properties and can always be computed even if there is no violation in the sample, whereas the Christoffersen test requires at least one violation to compute the test statistic.

In this study, the out-of-sample forecasts of VaR's are based on a rolling window estimation procedure. Firstly, the necessary parameters of the three models are estimated based on the latest 7 years (364 weeks) observations. The parameters are then fixed for one month (4 weeks) to facilitate out-of-sample interval forecasting. The estimation sample is then rolled ahead in increments of 4 weeks. The estimation and prediction procedure is repeated until the end of the observations. For example, to forecast the innovation distribution of the first 4 weeks of 2013, we use the data from 2006-2012 to estimate the parameters of interest, then in order to forecast the innovation distribution of the fifth-eighth weeks of 2013, the estimation sample period is moving forward 4 weeks, that is, from the fifth week of 2006 to the fourth week of 2013.

The results of the GMM conditional coverage test based on two moment conditions and a block size N equal to 25 are shown in Table 5. As expected, the normal GARCH method performs rather poorly in the VaR test at failure rate 1% as it fails 6/10 of the tests. The NM-AGARCH model also fails a few tests but gives the most accurate VaR forecast at failure rate 1% for wheat, broiler and butter. The NM-GARCH model achieves the best results for downside risk forecasting. With respect to 99% quantile forecasting, the normal GARCH model only passed the test for butter and nonfat dry milk. The NM-AGARCH model gives the worst 99% quantile prediction for wheat, cheddar and nonfat dry milk, possibly because the model is over-parameterized. The

NM-GARCH model achieves the best results for most commodities. In summary, the single-state normal GARCH model performs rather poorly especially with regards to the specification of skewness and kurtosis. The NM-AGARCH model that incorporates different component means and the additional leverage effect is found to fit better than the normal GARCH model but perform badly in out-of-sample forecasting, perhaps because of parameter proliferation. The NM-GARCH model with different component means achieves the best fit by all criteria.

5 Conclusion

Previous modelling of commodity price volatility assumes a single-state GARCH process and constant conditional skewness and kurtosis, and therefore is not able to detect the state dependent volatility dynamics if multiple states exist. Commodity price volatility may respond differently under different market states, for example, under the expectation of positive and negative price changes. The NM-type GARCH models allow for state-dependent volatility behavior and time-varying conditional skewness and kurtosis. Haas et al. (2004) and Alexander and Lazar (2009), among others, have applied those models in equity markets. This manuscript models agricultural commodity price volatility using the NM-GARCH models with the assumption of two market states.

Both in-sample and out-of-sample diagnostics are conducted to compare the fit of the NM-GARCH and the NM-AGARCH models with a normal GARCH specification. The overall conclusion is that the class of NM-GARCH models adequately capture relevant properties of agricultural commodity price data but the single-state normal GARCH model performs rather poorly especially regarding the specification of skewness and kurtosis. Contrary to the case in equity market as found in Alexander and Lazar (2009), the addition of dynamic asymmetry in the NM-AGARCH model is sometimes found unnecessary for a few commodities, as it disturbs the time series fit and upper tail prediction.

Empirical results on ten agricultural commodity cash prices find a clear relationship between expected price change and the volatility dynamics across regimes. For each of the ten commodities, expected negative price change corresponds to a greater volatility persistence, while expected positive price change arises in conjunction with an increasing responsiveness of volatility. This is just the opposite of the case in the equity markets, where Haas et al. (2004) found volatility is more persistent to positive shocks and more responsive to negative shocks.

Finally, when possible state-dependent "inverse leverage effects" are explicitly accounted for, as in the NM-AGARCH model, we found that for most commodities these effects are insignificant except on occasions when component means are negative. A significant inverse leverage effect is detected only for corn in a less frequently occurred regime where price falls are anticipated, which indicates the volatility in this regime tends to increase more following a realized price rise than a realized price drop. Conversely, beef is found to have significant leverage effects during the more frequent regime where prices are expected to fall, indicating a realized price fall would lead to higher volatility than a realized price recovery. By allowing state-dependent inverse leverage effects and volatility dynamics, two-state NM-GARCH models would facilitate more refined risk management practice than single-state GARCH models.

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