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A fishing expedition in the Mekong Delta: market volatility and price substitutes for Vietnamese fresh water fish

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Abstract

In this paper the Vietnamese fresh water fish product market is examined, using time series data from An Giang province in Vietnam, for the period from January 2004 to December 2005. Daily price volatility is analyzed using univariate Generalised Autoregressive Conditional Heteroskedasticity (GARCH). Subsequently, a Vector Autoregressive Model (VAR) is used to estimate the relationship between tra fish cultured in pond, tra fish cultured in cage, basa fish, tilapia and snakehead fish, and potential substitute products such as chicken, beef and pork.

1. Introduction

The Mekong Delta in Vietnam is renowned as a producer of fresh water fish, particularly for *Pangasius* with species like *basa (Pangasius bocourti)* and *tra fish (Pangasius hypophthalmus)*. The production boosted when the United States and Vietnam Bilateral Trade Agreement became effective in 2000. An Giang has been the leading province for fresh water fish products in the Mekong Delta for ten years.

Due to the increased quality and technological efficiency of *Pangasius* production, farmers in the An Giang province were able to meet the standards of domestic as well as foreign markets. However, the need for market research and analysis was acknowledged as prices were rather volatile. Moreover, in the United States, i.e. the main export market, the strong performance of Vietnamese fish farmers incited “protectionist” measures (e.g. the imposition of antidumping duties of 37% up to 57%[3]).

In this paper recent time series data on daily product prices are used to analyze price volatility of fresh fish products and to determine which potential substitute products have had a statistically significant impact on the prices of *Pangasius* fish products in the Mekong Delta in Vietnam.

2. Price volatility

The lack of stable prices for agricultural products has always been an important issue for developing countries, which often depend to a large extent on these products for their income. The desirability of price stability, to both consumers and producers, was explicitly acknowledged at the United Nations Conference on Trade and Employment held in Havana from November 1947 to March 1948. Article 57 of the final act of the conference states:

“*The members recognize that inter-governmental commodity agreements are appropriate for the achievement of the following objectives*:

[…]

(c) to prevent or moderate pronounced fluctuations in the price of a primary commodity with a view to achieving a reasonable degree of stability on a basis of such prices as are fair to consumers and pro-

vide a reasonable return to producers, having regard to the desirability of securing long-term equilibrium between the forces of supply and demand. “

However, the hopes of commodity agreements were largely disappointed and the focus of UNCTAD, the international organization involved in the coordination of commodity agreements, shifted to the analysis of market developments and the dissemination of market information,

UNCTAD (2004) reports on an expert meeting on financing commodity-based trade and development held in Geneva in November 2004, at which the lack of finance was diagnosed as a major impediment to the development of the agriculture sector in developing countries. Product quality concerns, high price volatility and the exigent requirements of purchasers are the main constraints linked to the market. As mentioned before, Vietnamese farmers increasingly succeed in meeting the quality standards for fresh fish products of domestic and foreign purchasers. The main constraint to investment in the fresh fish therefore seems to be the exposure to price volatility.

Commodity price volatility or uncertainty has been widely modeled within a GARCH framework, as originally developed by Engle (1982) and generalized by Bollerslev (1986). Aradhyula and Holt (1989), Holt (1993), Jayne and Myers (1994) used a GARCH model to analyze the volatility of commodity prices. According to Zheng, Jin and Leatham (2008), the extent to which food price news contributes to volatility may have some practical or policy interest. Tomek (2000) notes that the variance of farm prices increases from the harvest to summer, attributing the increase to crop uncertainty during the growing season.

In this section *Auto Regressive Conditional Heteroscedastic* (ARCH) models are used to determine the extent and characteristics of the volatility of fresh water fish in the Mekong Delta.

2.1 GARCH

Generalized ARCH models (GARCH), developed by Engle (1982) and generalized by Bollerslev (1986) are based on the assumption that forecasts of time-varying variance depend on lagged variance (i.e. autoregressive AR). An unexpected shock (positive or negative) at a given moment in time will increase variability in future periods.

A general GARCH *(p, q)* model can be written as:

$$r_t = \mu + \varepsilon_t \text{, with} \qquad \sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \qquad \alpha_i, \beta_j \geq 0 \qquad (1)$$

Where *p* refers to the degree of the autoregressive part and *q* to the number of lags of the shocks, μ is the mean value (expected to be zero) and σ_t^2 is a function of lagged values of ε_t^2 and ω.

In the simplest GARCH model, i.e. GARCH (1,1):

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \qquad (2),$$

[3] Vietnam Association of Seafood Exporters and Producers (VASEP), Final determination in the Anti-duping duty investigation of certain frozen fish fillets from Vietnam, www.ita.doc.gov/media/FactSheet/0603/catfish_final_061703.html

the coefficient α measures the influence of the volatility shock on the conditional variance whereas ($\alpha + \beta$) expresses the influence of the variability of variables from the previous period on the current value of the variability. This ($\alpha + \beta$) value is usually close to 1, which is a sign of increased inertia in the effects of shocks on variability.

2.2 EGARCH

In a number of time series, returns are found to be correlated with volatility, e.g. unexpected negative shocks have a bigger impact on variance than unexpected positive shocks. To take account of this potential asymmetry Nelson (1991) proposed a so-called Exponential GARCH model (EGARCH), in which conditional variance depends on both the size and the sign of shocks. An EGARCH (p,q) can be written as:

$$\log \sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \log \sigma_{t-j}^2 + \sum_{i=1}^{p} \left(\alpha_i \frac{|\varepsilon_{t-i}|}{|\sigma_{t-i}|} + \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right) \qquad (3)$$

and an EGARCH (1,1) as:

$$\log \sigma_t^2 = \omega + \beta \log \sigma_{t-1}^2 + \alpha \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \qquad (4)$$

Equation (4) allows positive and negative values of ε_t to have a different impact on volatility. The EGARCH model is asymmetric because the level $\frac{|\varepsilon_{t-i}|}{\sigma_{t-i}}$ is included with coefficient γ_i. If this coefficient is negative, positive shocks generate less volatility than negative return shocks, ceteris paribus (Premaratne and Bala, 2004).

2.3 TARCH

Threshold ARCH (TARCH) models were introduced independently by Zakoian (1990) and Glosten, Jaganathan and Runkle (1993) and offer an alternative to EGARCH to take account of the potential asymmetry between positive and negative shocks where effects are not assumed to be exponential as in EGARCH models.

A TARCH (p,q) model can be written in its general form as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \qquad (5)$$

and a TARCH (1,1) as:

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} + \beta \sigma_{t-1}^2 \qquad (6)$$

Where

$d_{t-1} = 1$, if $\varepsilon_{t-1} < 0$

$d_{t-1} = 0$, if $\varepsilon_{t-1} > 0$

An unforeseen increase in the return (i.e. good news) contributes to the variance in the model through α whereas an unforeseen decrease in the return generates an increase in volatility through ($\alpha + \gamma$). If γ differs from zero, shocks have an asymmetric impact and if $\gamma > 0$ a *leverage* effect exists.

2.4 Data

The data used in this study are daily prices (Vietnamese Dong/kg[4]) in the period from 1st January 2004 to 30th December 2005, provided by the Agricultural Extension Center of the Department of Agriculure and Rural Development in An Giang province. The following products are considered:

- **Fresh water fish**
  - Pondtra: Tra fish cultured in pond
  - Cagetra: Tra fish cultured in cage
  - Basa: Basa fish
  - Tilapia: Tilapia fish
  - Snakehf: Snakehead fish

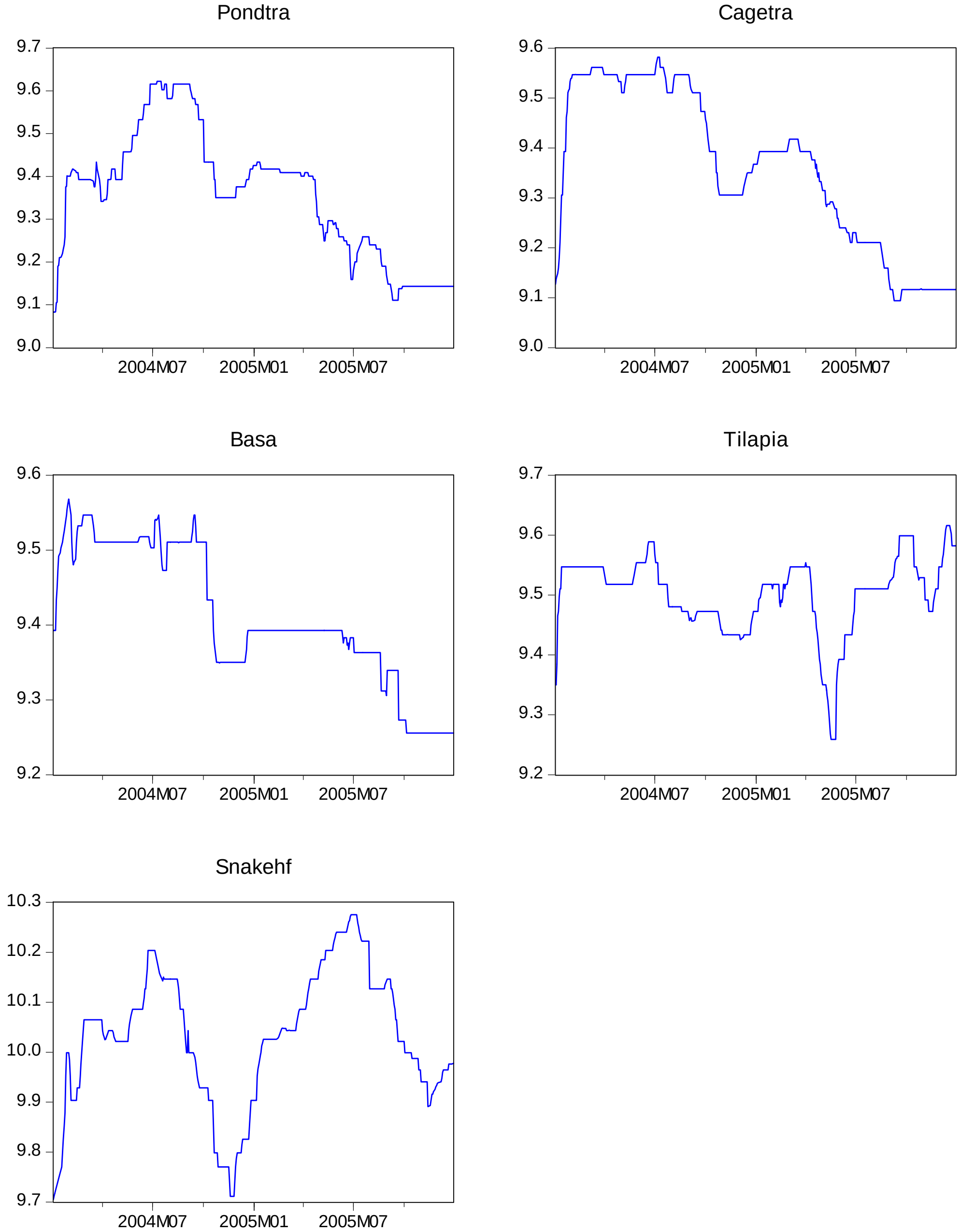
- **Livestock (substitute products)**
  - Chicken
  - Beef
  - Pork

[4] 1 USD = 15730 Vietnamese Dong (VND).

2.5 Empirical Results

The prices (natural logarithm) of freshwater fish are depicted in figure 1. Before analyzing the stationarity of the time series in section 2.5.2, possible outliers are tested for in section 2.5.1.

Figure 1: Prices (natural logarithm) of freshwater fish (2004-2005)



2.5.1 Testing and adjusting for outliers[5]

Following Plasmans (2006)

$$y_t = x_t + \omega I_t[t=\tau],\ t = 1, 2, 3,\ldots,T$$

With $I_t[t=\tau]$ an indicator dummy variable taking the value 1 when $t=\tau$ and 0 otherwise. The size of the outlier is denoted by ω.

$$x_t = \frac{\varphi(L)}{\alpha(L)}\varepsilon_t \qquad t = 1, 2, 3,\ldots,T$$

Where $\varphi(L)$ and $\alpha(L)$ are polynomials in *L*, with all roots of $\varphi(z)=0$ and those of $\alpha(z)=0$ outside the unit circle. A time series subject to the influence of an outlier y_t, can be described as follows:

$$y_t = x_t + \omega\frac{G(L)}{H(L)}I_t[t=\tau]$$

The impact of an outlier can be classified by imposing a special structure on $G(L)/H(L)$. The different types are an innovational outlier (*IO*), an additive outlier (*AO*), a level shift (*LS*) and temporary change (*TC*):

$$IO: \frac{G(L)}{H(L)} = \frac{\varphi(L)}{\alpha(L)}$$

$$AO: \frac{G(L)}{H(L)} = 1$$

$$LS: \frac{G(L)}{H(L)} = \frac{1}{(1-L)}$$

$$TC: \frac{G(L)}{H(L)} = \frac{1}{(1-\alpha L)}$$

As discussed by Chen and Liu (1993), the estimated residuals can be interpreted in terms of a regression model:

$$\hat{e} = \omega z_t + \varepsilon_t$$

Where in case of an additive outlier:

$$z_t = 0 \Leftrightarrow t \neq \tau \text{ except for } z_{t+k} = -\pi_k \Leftrightarrow t > \tau$$

$$z_t = 1 \Leftrightarrow t = \tau$$

Using possibly contaminated estimated residuals, $\hat{e}_t$, the $AR(\infty)$ model is given by:

$$\hat{e}_t = \hat{\pi}(L)y_t \text{ for } t = 1, 2,\ldots$$

[5] This section is to a very large extent based on Plasmans (2006).

The OLS estimator for the effect of a single outlier at $t = \tau$ can now be computed as:

$$\hat{\omega} := \hat{\omega}_{AO}(\tau) = \frac{\sum_{t=\tau}^{T} \hat{e}_t \hat{z}_t}{\sum_{t=\tau}^{T} \hat{z}_t^2}$$

Chang et al. (1988) show that a possible approach for detecting additive outliers is to examine the maximum value of the standardized statistic of the outlier effect:

$$\hat{\zeta}_{AO}(\tau) = \hat{\omega}_{AO}(\tau) / SE(\hat{\omega}_{AO}(\tau)),$$

where $SE(\hat{\omega}_{AO}(\tau)) := \hat{\sigma}_{\hat{\varepsilon}} \left(\sum_{t=\tau}^{T} \hat{z}_t^2\right)^{-1/2}$ is approximately normally distributed. The "omit-one" method, which implies calculating the standard deviation of the estimated residuals, leaving out the residual at period $t = \tau$, is used in this paper.

If $\hat{\zeta}_{AO}(\tau)$ exceeds a critical value C, the impact of the *AO* at period $t = \tau$ is considered to be statistically significant. The observed series y_t is then adjusted as follows:

$$y_t^{adj} = y_t - \hat{\omega}_{AO}(\tau) I_t [t = \tau]$$

Applying this method, the time series of pond tra, cage tra, basa, tilapia, snakehead fish and potential substitute products were tested for outliers. Some outliers were found in the time series, which where therefore adjusted following the aforementioned method.

2.5.2 Stationarity

Many economic variables are not stationary in levels but in (first) differences. To proceed with modeling it is important to determine the order of integration, i.e. the number of times a time series needs to be differenced to achieve stationarity. The order of integration of time series can be determined with unit root tests. The null hypothesis of these tests is that a given time series has a unit root which implies that it is not stationary. If the null hypothesis can be rejected the time series can be assumed to be stationary. In this paper, Dickey-Fuller, Phillips-Perron and Ng-Perron unit root tests are applied to identify the order of integration of the time series of the fish prices.

The Augmented Dickey and Fuller (ADF) test is given as (Dickey and Fuller, 1979):

$$\Delta y_t = \alpha_0 + \alpha T + \beta_0 y_{t-1} + \sum_{j=1}^{k} \beta_j \Delta y_{t-i} + e_{tk}$$

Where Δ is the difference operator and *T* is a time trend. The null hypothesis is that the series is not stationary. For the implementation of the ADF test it is important to specify the lag length *k*, which if taken too small will bias errors due to remaining serial correlation whereas if taken too large will reduce the power of the test.

The ADF and the Phillips-Perron (PP) tests are asymptotically equivalent but can differ substantially in finite samples as they correct for serial correlation in different ways. Schwert (1989) found that if Δy_t follows an ARMA process with a large and negative moving average (MA) component, the ADF and PP tests are severely size-distorted, resulting in the overrejection of the null hypothesis of no stationarity, with the PP tests being more distorted than the ADF tests.

Perron and Ng (1996) present three unit root tests (i.e. MZa, MZt, and MSB with MZt = MZa x MSB) collectively referred to as the *M* tests. The MZa and MZt tests provide a modified version of the Phillips (1987) and Phillips and Perron (1988) Z tests (Perron and Ng, 1998). The Perron and Ng (1998) test is far more robust to size distortions than other unit root tests, when the residuals have negative serial correlation. The Ng-Perron unit root test resolves the problem of low power and serious size distortion in the ADF and PP tests when the moving average component in the series y_t is significant and negative.

As shown in table 1, the null hypothesis of ADF and PP is rejected for tilapia and snakehead fish, suggesting stationarity in levels. However, for these two variables, the Ng-Perron null hypothesis of non-stationarity can not be rejected. Therefore it seems safe to assume that all time series are not stationary in levels. Unit root tests for the variables in first difference are reported in table 2. The null hypothesis is now clearly rejected for all tests and all variables. The results of the unit root tests seem to indicate that all variables considered are stationary in first differences, i.e. that all time series are integrated of order one.

Table 1 : Unit Root Tests (levels: $\log p_t$)

Variable	Augmented Dickey-Fuller t-Statistic	Phillips-Perron Adj. t-Statistic	Ng-Perron MZa	Ng-Perron MZt
Pondtra	-1.38 (0.59)	-1.46 (0.55)	-0.60	-0.54
Cagetra	-1.05 (0.74)	-1.34 (0.61)	-0.64	-0.56
Basa	-1.43 (0.57)	-1.01 (0.75)	-5.25	-1.48
Tilapia	-3.23 (0.02)**	-3.23 (0.02)**	-2.10	-0.84
Snakehf	-3.35 (0.01)**	-3.40 (0.01)**	-0.13	-0.11
Chicken	-2.28 (0.18)	-2.17 (0.22)	-1.73	-0.85
Beef	-1.97 (0.30)	-1.93 (0.32)	-4.22	-1.39
Pork	-1.95 (0.31)	-1.91 (0.33)	-0.36	-0.23

Note: P-values are given in brackets; The 1% critical values for the Ng-Perron MZa and MZt test are -13.80 and -2.58 respectively, the 5% critical values -8.10 and -1.98 respectively.
** significant at 5%.

Table 2 : Unit Root Tests (first differences: $R_t = \log(p_t / p_{t-1})$)

Variable	Augmented Dickey-Fuller t-Statistic	Phillips-Perron Adj. t-Statistic	Ng-Perron MZa	Ng-Perron MZt
Pondtra	-22.64 (0.00)***	-22.71 (0.00)***	-259.50	-11.40
Cagetra	-23.34 (0.00)***	-24.15 (0.00)***	-259.32	-11.39
Basa	-24.09 (0.00)***	-24.88 (0.00)***	-258.64	-11.37
Tilapia	-23.72 (0.00)***	-23.70 (0.00)***	-259.05	-11.38
Snakehf	-20.30 (0.00)***	-30.76 (0.00)***	-303.62	-12.32
Chicken	-25.08 (0.00)***	-25.08 (0.00)***	-257.05	-11.34
Beef	-22.62 (0.00)***	-22.67 (0.00)***	-259.49	-11.39
Pork	-23.57 (0.00)***	-23.62 (0.00)***	-19.33	-3.3

Note: P-values are given in brackets; The 1% critical values for the Ng-Perron MZa and MZt test are -3.80 and -2.58 respectively, the 5% critical values -8.10 and -1.98 respectively.
*** significant at 1%.

2.5.3 Results of GARCH models

The GARCH model requires a stationary data generating process. Unit root tests indicate that the prices of pond tra, cage tra, basa, tilapia and snakehead fish are not stationary in levels but stationary in first differences. First differences are therefore used for further analysis.

In table 3 the estimated autocorrelation functions (three first autocorrelations ρ_1, ρ_2 and ρ_3) are reported for log(P_t) – log(P_{t-1}), $\hat{y}_t$ denotes the estimated residuals, and $\hat{y}_t^2$ the squared residuals.

As shown in table 3, there is substantial autocorrelation in the third lag of pond tra, in the first three lags of cage tra, in the first two lags of basa, and autocorrelation in the first lag for tilapia but no autocorrelation in the first three lags for snakehead fish. The results in the second panel (EACF of $\hat{y}_t^2$) of table 3 suggest that *q* may equal 1 or 2 (as only the first two estimated autocorrelations of $\hat{y}_t^2$ are significant) for cage tra and basa, while *q=1* seems to apply to the other time series.

Table 3 : Estimated autocorrelation functions (EACF)

Series	$\hat{\rho}_1$	$\hat{\rho}_2$	$\hat{\rho}_3$
EACF of R_t			
Pondtra	0.00	-0.07	0.09**
Cagetra	0.58**	0.16**	0.09**
Basa	0.58**	0.12**	0.02
Tilapia	0.30**	0.06	0.04
Snakehf	0.01	0.02	0.05
EACF of $\hat{y}_t^2$	$\hat{\rho}_1$	$\hat{\rho}_2$	$\hat{\rho}_3$
Pondtra	0.16**	0.07	0.00
Cagetra	0.10**	0.10**	0.04
Basa	0.10**	0.13**	0.06
Tilapia	0.20**	-0.03	0.04
Snakehf	0.32**	0.08	0.07

Note:** significant at 5%.

A Lagrange Multiplier (LM) test considers the null hypothesis of no ARCH *(q)* versus the alternative hypothesis that the errors are given by a GARCH *(p,q)* process (Engle, 1982). Because the data of daily time series represent working days (i.e. Monday to Friday), the LM is used to test for the first day and the fifth day. The results in table 4 suggest that *q* is larger than 1 for all time series.

Based on the Ljung-Box Pierce portmanteau test (Box and Pierce, 1970), the null hypothesis of conditional homoskedasticity can be rejected for all five time series. The slow decline of the autocorrelation function of the squared residuals suggests that a GARCH(1,1) process may be suitable for describing the errors, whereas a low order ARCH process may not fully capture the time-varying volatility in the data.

Table 4: Parameter estimates from fitting AR*(p)*

AR model	Pondtra	Cagetra	Basa	Tilapia	Snakehf
AR(1)		0.83*	0.77*	0.30*	
AR(2)		-0.48*	-0.33*		
AR(3)	0.09***	0.23*			
AIC	-6.94	-8.40	-7.45	-6.07	-5.68
SC	-6.92	-8.37	-7.42	-6.06	-5.67
LL	1795.78	2175.58	1932.11	1578.36	1478.59
$Q^2(12)$	30.41*	22.71*	44.41*	37.28***	66.65**
LM ARCH(1)	13.70(0.00)	4.96(0.03)	9.49(0.03)	21.35(0.00)	60.80(0.00)
LM ARCH(5)	4.07(0.00)	2.36(0.04)	2.53(0.03)	6.35(0.00)	54.62(0.02)

Note: AIC: Akaike Info Criterion; SC: Schwarz Criterion; LL: Log Likelihood; LM: Lagrange Multiplier tes; $Q^2(12)$ Ljung-Box-Pierce portmanteau test for up to twentieth order serial correlation in the residuals and the squared residuals respectively. P-values are given in brackets.
*** significant at 1%; ** significant at 5%; * significant at 10%.

In sum, the GARCH(1,1) seems the most appropriate to estimate the five time series. In table 5 the results of the estimation of a GARCH, TARCH and EGARCH model are reported.

(i) Tra fish cultured in pond: α, β and γ are all highly significant for all models. In the EGARCH model γ is positive which implies that a positive price shock results in higher volatility than a negative price shock. The γ coefficient in the TARCH model is –0.26 which is less than 0 and is significant. This means that the impact of news is asymmetric in the market for tra fish cultured in pond but that there does not appear to be leverage. The magnitude of the differential impact on conditional variance can be ascertained from α and γ. Good news for the pond tra fish market has an impact of 0.36 while the impact of bad news on the conditional variance is given by 0.10 ($\alpha + \gamma$).

The AIC/SC criteria and the Log Likelihood values suggest that EGARCH is the preferred model.

The fact that $\alpha + \beta$ (0.93) in the GARCH model is close to 1 indicates that for tra fish cultured in pond a shock has a persistent impact on volatility.

(ii)Tra fish cultured in cage: α and β are highly significant in the GARCH model. The γ coefficient is significant and positive in TARCH, which points at a *leverage effect*. The sum of $\alpha + \beta$ (0.83) in the GARCH model is somewhat smaller than 1, suggesting some persistence in the impact on volatility. Unlike for tra fish cultured in pond, the AIC/SC criteria and Log Likelihood indicate that TARCH is preferred to model the volatility of prices of tra fish in cage.

Table 5: Estimation results of GARCH(1,1), TARCH and EGARCH

Statistic	GARCH(1,1)	TARCH	EGARCH
Tra in pond			
AR (3)	0.08	0.08	0.09
α_1	0.19***	0.36***	0.38***
β_1	0.74***	0.64***	0.83***
γ_1	-	-0.26***	0.11***
AIC/SC	-7.13/-7.09	-7.14/7-7.09	**-7.17/-7.11**
Log Likelihood	1847.36	1851.06	**1858.55**
Tra in cage			
AR (1)	0.62***	0.68***	0.35*
AR (2)	-0.31***	-0.39***	-0.19*
AR (3)	0.13	0.18**	0.17*
α_1	0.11***	0.02	0.58.*
β_1	0.72***	0.83***	0.12
γ_1	-	0.07***	-0.08
AIC/SC	-8.50/-8.44	**-8.50/-8.44**	-8.46/-8.40
Log Likelihood	2199.69	**2202.15**	2190.78
Basa			
AR (1)	0.68	0.69***	0.71***
AR (2)	-0.28	-0.29***	-0.34***
α_1	0.09***	0.12***	0.20***
β_1	0.89***	0.89***	0.95
γ_1	-	-0.04*	-0.01
AIC/SC	-7.85/-7.80	-7.85/-7.79	**-7.88/-7.83**
Log Likelihood	2039.96	2040.17	**2048.72**
Tilapia			
AR (1)	0.27***	0.24***	0.25***
α_1	0.05***	0.02*	0.32***
β_1	0.81***	0.86***	-0.64***
γ_1	-	0.07***	0.17***
AIC/SC	-6.14/-6.10	-6.15/-6.10	**-6/16/-6/11**
Log Likelihood	1599.22	1601.65	**1605.10**
Snakehead fish			
α_1	0.28***	0.30***	0.46***
β_1	0.22***	0.22***	0.37***
γ_1	-	-0.04	0.003
AIC/SC	**-5.87/-5.83**	-5.86/-5.82	-5.86/-5.82
Log Likelihood	**1529.31**	1529.30	1528.85

Note: ***, ** and-* denotes significance at 1%, 5% and 10% respectively.

(iii) *Basa:* α, β and γ are significant in all models, except for β and γ in the EGARCH model. The γ coefficient in the TARCH model is –0.04 which is less than 0 and is significant, indicating that the impact of news is asymmetric in the basa market but that there is no evidence of a leverage effect. A positive price shock for basa has an impact of 0.12 whereas the impact of a negative price shock has an impact of 0.08 ($\alpha + \gamma$). In the GARCH model ($\alpha + \beta$) is 0.99 (i.e. very close to 1), which means that the impact on volatility is very persistent. AIC/SC and Log Likelihood suggest to consider EGARCH as the preferred model.

(iv) Tilapia: α, β and γ are highly significant in all models. A *leverage effect* is suggested by the positive value of γ in TARCH. Good news has an impact of 0.02 and bad news an impact of 0.07 ($\alpha + \gamma$).

The positive sign of γ in the EGARCH model indicates that a positive price shock of tilapia results in higher volatility than a negative price shock. The sum of $\alpha + \beta$ (0.86) in the GARCH suggests the persistence of the impact of price shocks on volatility. AIC/SC and the maximum Log Likelihood value designate EGARCH as the preferred model.

(v) Snakehead fish: α and β are highly significant in all models, while γ is negative in TARCH and positive in EGARCH, though both not significant. The sum $\alpha + \beta$ (0.50) in the GARCH model does not suggest that shocks have a persistent effect on volatility. Once again, AIC/SC and Log Likelihood designate GARCH as the preferred model.

Following Zheng, Kinnucan and Thompson (2008) the EGARCH model is used to estimate the effect of news on the volatility of daily prices. The results are shown in table 6. In the EGARCH model the effect of high price news on conditional variance is $\alpha + \gamma$ and the low price effect is $\alpha - \gamma$. For tra raised in pond, the estimated effects are 0.49 and 0.27. An unexpected price increase measured by a unit increase in the standardized residual $\left|\varepsilon_{t-1}\right| / \sigma_{t-1}$ with ε_{t-1}>0 increases volatility approximately by 49%. In contrast, an unexpected price decrease increases volatility by 27%. There is a similar pattern for tilapia and snakehead fish, but in contrast, for tra raised in cage and basa an unexpected price increase- measured by a unit increase- increases volatility by approximately 50% and 19% respectively, whereas an unexpected price decrease increase volatility by 66% and 21% respectively.

Table 6: Effect of price shocks on the volatility of prices

Variable	Coefficient γ	High price news (positive shock) ($\alpha + \gamma$)	Low price news (negative shock) ($\alpha - \gamma$)
Tra in pond	0.11**	0.49	0.27
Tra in cage	-0.08	0.50	0.66
Basa	-0.01	0.19	0.21
Tilapia	0.17**	0.49	0.15
Snakehead	0.003	0.46	0.45

Note: ** significant at 5%.

In table 7 the results are given of a test of the persistence of price shocks, i.e. $\alpha + \beta = 1$ (GARCH). The hypothesis is clearly rejected for all five time series. On the whole, basa and the tra cultured in pond show the highest persistence of an impact on volatility, which means that their markets are the most vulnerable to price shocks. To a lesser extent this also applies to the tilapia and cage tra fish market, whereas the snakehead fish market does not appear to be very sensitive to price shocks.

Table 7: Test of $\alpha + \beta = 1$ in the GARCH model

Variable	Preferred model	Coefficient in GARCH $(\alpha + \beta)$	Coefficient test Ho: $\alpha + \beta = 1$
Tra in pond	EGARCH	0.93	Rejected
Tra in cage	TARCH	0.83	Rejected
Basa	EGARCH	0.99	Rejected
Tilapia	EGARCH	0.86	Rejected
Snakehead	GARCH	0.50	Rejected

Note: The hypothesis is rejected at the 1% significance level

3. Price substitutes

The Vector Auto-Regressive Model (VAR) was first proposed by Sims (1980), who argued that conventional structural models involve incredible identifying restrictions whereas VAR can be used to analyze empirical relationships between time series.

VAR imposes few theoretical assumptions on the structure of a model. With a VAR, one needs to specify only two things (Pindyck and Rubinfeld, 1991): (i) the *set of variables* (endogenous and exogenous) that is believed to interact and hence should be included, and (ii) the *largest number of lags* that are needed to capture most of the effects that the variables have on each other. The equations of the model are constrained to be linear so one need not worry about functional forms.

A general VAR model with n linear equations (x_1, x_2, ..., x_n the endogenous variables and z_1, z_2, ..., z_n the exogenous variables) is given by:

$$x_{1,t} = a_{10} + \sum_{j=1}^{p} a_{11j} x_{1,t-j} + \sum_{j=1}^{p} a_{12j} x_{2,t-j} + \ldots + \sum_{j=1}^{p} a_{1nj} x_{n,t-j}$$
$$+ \sum_{j=0}^{r} b_{11j} z_{1,t-1} + \ldots + \sum_{j=0}^{r} b_{1mj} z_{m,t-j} + \varepsilon_{1t}$$

$$x_{n,t} = a_{n0} + \sum_{j=1}^{p} a_{nj} x_{1,t-j} + \sum_{j=1}^{p} a_{n2j} x_{2,t-j} + \ldots + \sum_{j=1}^{p} a_{nnj} x_{n,t-j}$$
$$+ \sum_{j=0}^{r} b_{n1j} z_{1,t-1} + \ldots + \sum_{j=0}^{r} b_{nmj} z_{m,t-j} + \varepsilon_{nt}$$

Here, *p* is the number of lags of the endogenous variables, and *r* the number of lags of the exogenous variables. As there are no unlagged endogenous variables on the right-hand side and the right-hand side variables are the same in each equation, OLS provides a consistent and efficient estimator (Pindyck and Rubinfeld, 1991).

Choosing *p* and *r*, the lags should be long enough to fully capture the dynamics of the system. On the other hand, the longer the lags are the greater the number of parameters to be estimated, and the fewer the degrees of freedom.

Variance decompostion and impulse response functions reveal the dynamic interactions and the strength of causal relations among the variables considered. Variance decomposition indicates the percentage of a variable's error variance that can be attributed to shocks (own shocks and shocks to other variables). Impulse response functions show the directional response of a variable to a one standard deviation shock in other variables. By capturing both direct and indirect effects of shocks on a variable of interest these functions permit to analyze in detail the dynamic linkages in the system (Ibrahim, 2007).

3.1 The results of the VAR model

The endogenous variables presented in the VAR model are the prices of fresh water fish products (pond tra, cage tra, basa, tilapia and snakehead fish) and livestock (chicken, beef and pork). Some outliers were found in the daily price of livestock products, so the adjusted time series (see section 2.5.1) are used in the VAR model. As for all variables the null hypothesis of no stationarity can be rejected for first differences, these are used in the model.

Krolzig (1996) and Lütkepohl and Saikkonen (1997) use four different criteria: Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SC) and Hannan-Quinn Information (HQ) to specify the order of the VAR (see Lütkepohl, 1991). Results for a lag order up to 8 are reported in table 8.

According to Lütkepohl and Saikkonen (1997), choosing *h* somewhat smaller than $T^{1/3}$ would be a possibility suggested by the upper bound $h \sim o(T^{1/3})$. For T=511, this implies an order h< 8 ($511^{1/3}$), meaning that any order of the VAR below 8 is possible. As shown in table 8, based on the different criterions VAR(1), VAR(2) and VAR(3) are candidates. According to Kamaly and Erbil (2001), if a given lag has the lowest AIC and SC then that lag is used. If, however, one criterion increases while the other one decreases as the number of lags rises, then the likelihood ratio can be used to determine the right lag.

The SC criterion favours order 1. As lag order 2 is suggested by FPE, AIC as well as HQ a VAR(2) model appears to be the most appropriate.

In what follows the results of Granger Causality tests are reported for VAR(1), VAR(2) and VAR(3). The preferred VAR(2) model, is discussed in more detail.

Table 8: Lag order selection of the VAR model

Lag	LogL	LR	FPE	AIC	SC	HQ
0	12935.65	NA	1.47e-32	-50.60	-50.53	-50.57
1	13315.29	745.91	4.26e-33	-51.83	-51.24*	-51.59
2	13464.06	287.65	3.06e-33*	-52.165*	-51.04	-51.73*
3	13515.55	97.93*	3.21e-33	-52.11	-50.46	-51.46
4	13559.45	82.14	3.48e-33	-52.04	-49.85	-51.18
5	13593.17	62.02	3.92e-33	-51.92	-49.19	-50.85
6	13620.33	49.11	4.54e-33	-51.77	-48.52	-50.50
7	13657.51	66.07	5.06e-33	-51.67	-47.89	-50.19
8	13691.93	60.07	5.70e-33	-51.55	-47.24	-49.86

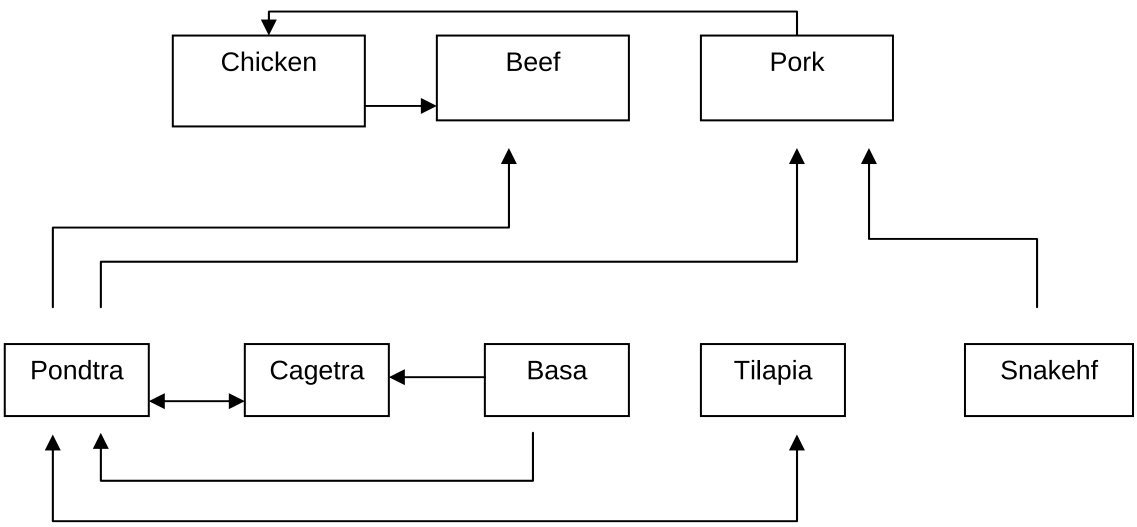
Note : * indicates the lag order selected by the criterion; LR: sequential modified LR test statistic; FPE: Final prediction error; AIC: Akaike information criterion; SC: Schwarz information criterion; HQ: Hannan-Quinn information criterion.

Granger Causality

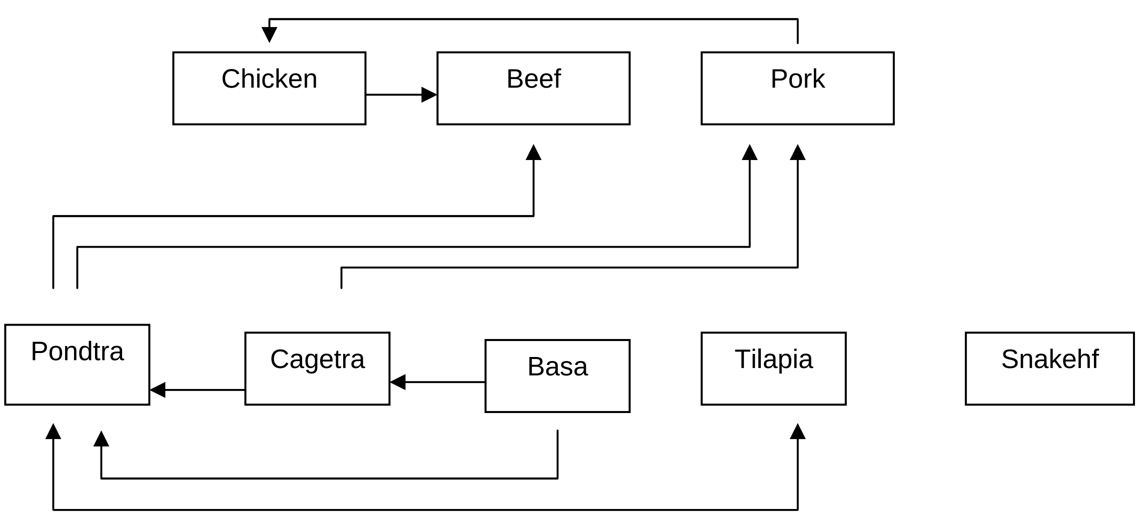
Granger (1969) investigated the causal relations between two (or more) variables. Several Granger causality tests have been proposed and studies have considered their applicability (see e.g. Hamilton, 1994). The results of Granger causality tests are presented in Appendix 1. There are eleven pairs of significant causal relationships for VAR(1), ten pairs for VAR(2), and eight pairs for VAR(3). These causal relations are drawn in figures 2 a,b,c. In the VAR(1) model, the price of tra raised in pond is affected by the price of basa and tilapia. There is evidence of bi-directional causality between tilapia and pond tra and between pond tra and cage tra and evidence of uni-directional causality from pond tra to beef and pork. Uni-directional causality runs from basa to cage tra. The price of chicken is affected by the price of pork and the latter by prices of pond tra and snakehead fish (see figure 2a).

Figure 2: Causal relationships in the VAR models

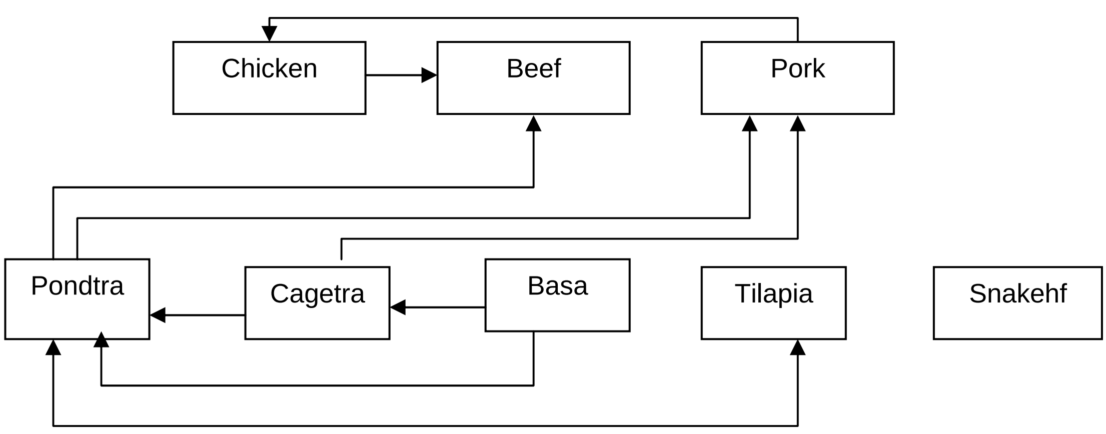
a. VAR(1) model



b. VAR(2) model



c. VAR(3) model



For the VAR(2) model, the causal relations are depicted in figure 2b. There appears to be evidence of uni-directional causality that runs from basa to tra raised in pond and cage; uni-directional causality from pond tra to beef and pork and of bi-directional causality between tilapia and tra raised in pond. Unlike in the VAR(1) model, the price of pork is affected by tra raised in pond and cage and the price of tra raised in pond by the price of tra raised in cage and basa.

Causal relations for VAR(3) are depicted in figure 2c. Evidence indicates uni-directional causality from basa to tra raised in pond and cage and uni-directional causality from tra raised in pond to beef and pork. As in the VAR(2) model, the price of pork is influenced by the price of tra raised in pond and cage, whereas the price of beef is influenced by the price of chicken and tra raised in pond and the price of chicken by the price of pork.

The results of VAR(2) and VAR(3) are very similar, except for the evidence of bi-directional causality between tilapia and tra raised in pond in the VAR(2), which is not found in the VAR(3).

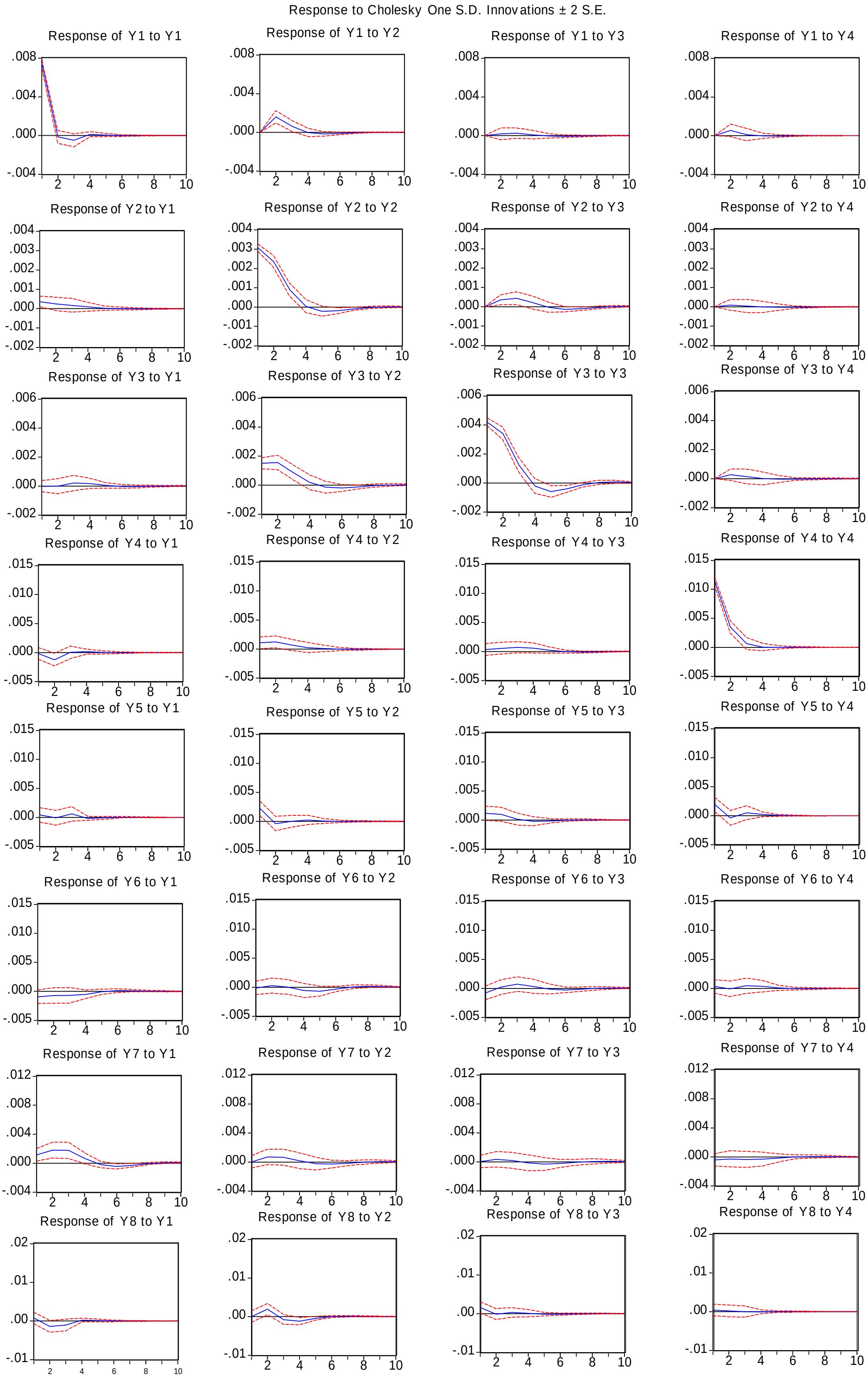
Following Yang, Jin and Leatham (2003), generalized forecast error variance decomposition and generalized impulse response analysis is applied to summarize the price transmissions between the different markets. Originally developed by Koop et al. (1996) and Pesaran and Shin (1998), these techniques can circumvent the dependence of the orthogonalized forecast error variance decomposition and impulse response analysis of the ordering of variables in the VAR. The decomposition of Babula, Bessler and Payne (2003) of forecast error variance is closely related to Granger causality analysis as they both analyze causal relationship between two variables. As the variance decomposition of an endogenous variable is considered for alternative horizons to shocks in each variable (including itself), forecast error variance decomposition provides evidence of the existence of a relationship between two variables, but it also illuminates the strength and the dynamics of this relationship (Bessler, 1984; Babula and Rich, 2001; Sagharian et al., 2002). The results of variance decomposition for 5, 10 and 15 days horizons respectively are presented in Appendix 2. A leading market is one of which the variance of its price can explain a large percentage of the error variance of other markets while its own forecast error is not explained by shocks in other markets (Premaratne and Bala, 2004).

Because VAR(2) is the preferred model, the discussion below will concentrate on variance decomposition and impulse response analysis for this model.

Most of the commodity prices (tra raised in pond, tra raised in cage, tilapia, snakehead fish, chicken, beef and pork) explain themselves for more than 90%, except for basa (about 81%).

For a 15 days horizon, the price of tra raised in cage explains more than 5% of price variation of tra raised in pond. As mentioned before, tra raised in pond and tilapia have a bi-directional causal relation, but tra raised in pond explains price variation in the tilapia market twice as much as the tilapia market evolution explains variation of tra raised in pond, suggesting that the latter is the price leader. Tra raised in cage seems to be a price leader for the basa market as it explains some 17% of price variation of basa. Price movements of tra raised in cage, basa and tilapia have an impact on the price of tra raised in pond. Tra cultured in pond and in cage affect the price of potential substitute products beef and pork. In contrast, the potential substitute products do not seem to have a statistically significant impact on the price of fresh water fish (see figure 3).

Figure 3: Impulse response function of price shocks in the fresh water fish market and the market of substitute products VAR(2)



Note: Y1 = Pondtra; Y2 = Cagetra; Y3 = Basa; Y4 = Tilapia; Y5 = Snakehf; Y6 = Chicken;Y7 = Beef; Y8 = Pork

4. Conclusion

In this paper price, volatility of fresh water fish products (tra raised in pond and in cage, basa, tilapia and snakehead fish) in he Mekong Delta in Vietnam is analyzed as well as the relationships between prices of fresh water fish and potetial substitute products such as chicken, beef and pork.

The estimation results of a number of models considering autoregression and conditional heteroscedasticity (i.e. GARCH; EGARCH and TARCH) indicate that price shocks have a persistent impact on volatility for basa, tra raised in pond and in cage and tilapia. Basa and tra cultured in pond appear to be the more vulnerable to price shocks than tilapia and tra cultured in cage whereas price shocks of snakehead fish do not seem to have a persistent impact on volatility. Positive price shocks of tra raised in pond and tilapia have a higher impact on volatility than negative price shocks, indicating a so-called leverage effect.

The results of the estimation of a Vector Autoregression (VAR) model suggest that tra raised in cage is a price leader for basa and to a lesser extent for tra raised in pond. In addition to tra raised in cage, prices of basa and tilapia also seem to affect the price of tra raised in pond. Tra cultured in pond and tilapia share a mutual causal price relationship.

Potential substitute products as beef, chicken and pork do not appear to have a significant effect on prices of fresh water fish. On the other hand, the price of tra raised in pond and in cage affect the price of beef and pork. The price of chicken responds to price shocks of pork whereas the price of beef responds significantly to price shocks of chicken.

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APPENDICES

Appendix 1: Granger Causality Test, VAR(p) *p* = 1, 2 and 3

Null hypothesis	VAR(1)		VAR(2)		VAR(3)	
	F-statistic.	p-value.	F-statistic.	p-value.	F-statistic.	p-value.
y2 ---×----> y1	27.42	**0.00**	16.03	**0.00**	11.50	**0.00**
y1 ---×----> y2	3.32	**0.07**	1.48	0.23	0.97	0.41
y3 ---×----> y1	8.79	**0.00**	4.52	**0.01**	2.95	**0.03**
y1 ---×----> y3	0.39	0.53	0.53	0.59	0.19	0.90
y4 ---×----> y1	6.57	**0.01**	3.03	**0.04**	1.99	0.11
y1 ---×----> y4	4.59	**0.03**	2.47	**0.09**	1.63	0.18
y5 ---×----> y1	1.83	0.18	1.03	0.36	1.40	0.24
y1 ---×----> y5	0.01	0.93	0.51	0.60	0.31	0.82
y6 ---×----> y1	0.14	0.71	1.41	0.24	1.06	0.37
y1 ---×----> y6	0.14	0.71	0.72	0.49	0.78	0.50
y7 ---×----> y1	0.22	0.64	0.50	0.61	1.40	0.24
y1 ---×----> y7	4.76	**0.03**	3.08	**0.04**	2.60	**0.05**
y8 ---×----> y1	0.10	0.75	0.14	0.87	0.31	0.82
y1 ---×----> y8	3.92	**0.04**	3.49	**0.03**	2.33	**0.07**
y3 ---×----> y2	3.23	**0.07**	2.53	**0.08**	2.14	**0.09**
y2 ---×----> y3	0.78	0.38	1.22	0.30	0.87	0.46
y4 ---×----> y2	1.22	0.27	1.40	0.25	1.92	0.13
y2 ---×----> y4	0.72	0.40	1.59	0.21	0.98	0.40
y5 ---×----> y2	2.11	0.15	0.48	0.62	1.25	0.29
Y2 ---×----> y5	0.11	0.75	0.60	0.55	0.34	0.79
y6 ---×----> y2	0.11	0.74	0.39	0.67	0.25	0.86
y2 ---×----> y6	0.36	0.55	2.06	0.13	1.79	0.15
y7 ---×----> y2	0.06	0.81	0.20	0.82	0.23	0.88
y2 ---×----> y7	1.79	0.18	1.54	0.22	1.96	0.12
y8 ---×----> y2	0.54	0.46	0.84	0.43	1.08	0.36
y2 ---×----> y8	0.49	0.48	4.13	**0.02**	3.19	**0.02**
y4 ---×----> y3	0.33	0.57	1.77	0.17	1.98	0.12
y3 ---×----> y4	1.31	0.25	0.71	0.49	0.66	0.58
y5 ---×----> y3	1.85	0.17	1.07	0.34	0.75	0.52
y3 ---×----> y5	1.47	0.23	1.15	0.32	1.14	0.33
y6 ---×----> y3	0.28	0.60	0.07	0.94	0.46	0.71
y3 ---×----> y6	1.12	0.29	0.45	0.64	0.32	0.81
y7 ---×----> y3	1.18	0.28	0.28	0.76	0.25	0.86
y3 ---×----> y7	1.36	0.24	1.24	0.29	1.76	0.15
y8 ---×----> y3	0.11	0.74	0.38	0.68	0.36	0.78
y3 ---×----> y8	0.40	0.53	1.36	0.26	1.45	0.23
y5 ---×----> y4	1.86	0.17	1.07	0.34	1.02	0.38
y4 ---×----> y5	0.24	0.63	0.66	0.52	0.80	0.49
y6 ---×----> y4	0.35	0.55	1.00	0.37	0.59	0.62
y4 ---×----> y6	0.01	0.92	0.44	0.64	0.66	0.58
y7 ---×----> y4	0.03	0.87	0.08	0.92	0.23	0.88
y4 ---×----> y7	0.01	0.91	0.35	0.70	0.40	0.75
y8 ---×----> y4	0.13	0.71	0.70	0.49	0.88	0.45
y4 ---×----> y8	0.16	0.69	0.17	0.84	0.13	0.94
y6 ---×----> y5	0.04	0.84	0.08	0.92	0.40	0.75
y5 ---×----> y6	0.35	0.55	1.29	0.28	1.38	0.25
y7 ---×----> y5	1.27	0.26	0.65	0.52	0.84	0.47
y5 ---×----> y7	0.03	0.85	0.28	0.76	0.63	0.60
y8 ---×----> y5	0.47	0.50	0.65	0.52	1.15	0.33
y5 ---×----> y8	3.08	**0.08**	1.67	0.19	1.08	0.36
y7 ---×----> y6	0.44	0.51	1.33	0.27	1.02	0.38
y6 ---×----> y7	8.19	**0.00**	5.51	**0.00**	3.68	**0.01**
y8 ---×----> y6	7.43	**0.01**	6.48	**0.00**	4.67	**0.00**
y6 ---×----> y8	0.04	0.84	0.32	0.72	0.87	0.45
y8 ---×----> y7	0.09	0.77	0.21	0.81	0.13	0.94
y7 ---×----> y8	0.33	0.57	0.56	0.57	0.57	0.64

Note:
y1=Pondtra; y2 = Cagetra; y3 = Basa; y4 = Tilapia; y5 = Snakehf; y6 = Chicken ; y7 = Beef; y8 = Pork;
Bold numbers mean that the null hypothesi of no causality is rejected at 5% significant level.
---×----> means "does not Granger Cause"

Appendix 2: Generalized forecast error variance decomposition for VAR(2)

Period	S.E.	Pondtra	Cagetra	Basa	Tilapia	Snakehf	Chicken	Beef	Pork
Variance Decomposition of Tra raised in pond									
5	0.01	92.65	5.70	0.24	0.50	0.20	0.47	0.13	0.11
10	0.01	92.61	5.70	0.25	0.50	0.20	0.49	0.13	0.11
15	0.01	92.61	5.70	0.25	0.50	0.20	0.49	0.13	0.11
Variance Decomposition of Tra raised in cage									
5	0.01	2.01	96.06	1.21	0.30	0.15	0.11	0.05	0.10
10	0.01	2.01	95.97	1.28	0.31	0.15	0.11	0.06	0.10
15	0.01	2.01	95.97	1.28	0.31	0.15	0.11	0.06	0.10
Variance Decomposition of Basa									
5	0.01	0.30	17.04	81.13	0.41	0.53	0.03	0.33	0.23
10	0.01	0.30	17.05	81.05	0.41	0.54	0.04	0.36	0.25
15	0.01	0.30	17.05	81.05	0.41	0.54	0.04	0.36	0.25
Variance Decomposition of Tilapia									
5	0.012	1.126	2.708	0.130	94.806	0.395	0.264	0.070	0.500
10	0.012	1.126	2.726	0.133	94.767	0.397	0.271	0.076	0.504
15	0.012	1.126	2.726	0.133	94.767	0.397	0.271	0.076	0.504
Variance Decomposition of Snakehead fish									
5	0.01	0.29	2.10	1.23	2.00	93.84	0.03	0.35	0.17
10	0.01	0.29	2.10	1.23	2.00	93.82	0.03	0.36	0.17
15	0.01	0.29	2.10	1.23	2.00	93.82	0.03	0.36	0.17
Variance Decomposition of Chicken									
5	0.02	0.95	0.87	0.50	0.17	0.35	94.00	0.51	2.64
10	0.02	0.96	0.95	0.55	0.17	0.36	93.78	0.56	2.68
15	0.02	0.96	0.95	0.55	0.17	0.36	93.78	0.56	2.68
Variance Decomposition of Beef									
5	0.01	4.89	0.34	0.40	0.24	0.66	2.80	90.55	0.12
10	0.01	5.01	0.38	0.46	0.24	0.66	2.93	90.18	0.14
15	0.01	5.01	0.38	0.46	0.24	0.66	2.93	90.17	0.14
Variance Decomposition of Pork									
5	0.02	1.23	1.70	1.13	0.13	0.54	0.17	0.18	94.93
10	0.02	1.23	1.70	1.14	0.13	0.54	0.17	0.18	94.91
15	0.02	1.23	1.70	1.14	0.13	0.54	0.17	0.18	94.91