The nature of volatility in temporal profit with in Ethiopian commodity exchange: The case of washed export coffee modelled using ARFIMA-M-HYGARCH model

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Introduction

Ethiopian commodity exchange opened for business in April 24, 2008 (Eleni, 2012). Trading in coffee, though, was started in December 2, 2008 (ibid). Ethiopian Commodity exchange is government owned exchange (Federal Negarit Gazeta, 2008) and despite the wider allegation to make it as issue (see Eleni, 2012), it is fact that government ownership or private ownership does not affect the efficiency of commodity exchange.

First, the most successful commodity exchanges in the last 20 to 30 years are found in China and are government owned (Rutten, 2005). And many experiments to start commodity exchange by private sector in many East European countries and many African countries, in the same period, were not found to be successful. (Santana-Boado and Brading, 2000). What matters for success is independence of management not the nature ownership (Taddese, 2006). As long as the management is independent of political pressure and guided by efficient managerial principles, ownership does not matter. The problem with Ethiopian Commodity Exchange is not ownership but questions may be raised on the independence of the management from informal political pressure and the fact that participation in commodity exchange is not an optional for traders but legal duty in order to export (see Federal Negarit Gazeta, 2008). Legally Ethiopian commodity exchange is independent in terms of management (Eleni, 2012 and Federal Negarit Gazeta, 2008). But by being government sponsored exchange it can exercise informal powers on traders and traders could take it for government agency and as result can easily fear it. But at the same time it is hard to imagine with in Ethiopian political economy that the informal pressures from state will not influence the decision of the commodity exchange, especially when board chairman is state minster (see Eleni, 2012 for composition of board members). After making qualitative survey of coffee value chain Molina (2010) observed that

> *"Although measuring the extent to which political affiliation affects the relations between the actors in the chain was quite beyond the possibilities of this study, a contained tension between the government and certain chain actors was evident. This tension was most noticeable in interviewees' refusal to comment or in statements such as: 'the system is new and it has to evolve and adapt to address the actor's concerns'. Criticism to the Government is commonly expressed through blogs and newspaper articles, especially from the Ethiopian Diaspora."* (page, 42)

This is clearly shows informal pressures, perceived or real does not matter, are there. Moreover, as is stated by Eleni (2012) many commodities around the world are traded in specific exchange, as coffee in Ethiopia is traded within ECX only. However it is missing one big fact that in other commodity exchanges, you are not legally obliged to use this specific commodity exchange. For example a study by Gebrekiros (2011) found that transaction cost in ECX is greater than the old auction system for more than 60% of the participants. Means if they are not forced by law to do so, they would not use it.

Second at the start of the exchange most traders did make it clear, they will not participate in the exchange, unless it is under government ownership. They seem to trust the legal power of the state than the socio capital they accumulate among themselves. By being member of the commodity exchange task force which made the preliminary study, the author is able to observe the response of different traders and trade associations for this issue. This is reported in unpublished report submitted to Ministry of Agriculture in Eleni et al (2006).

The most serious problems with current commodity exchange can be grouped in to two. First, it was able to destroy any possibility for speciality coffee in organic niche market which demands traceability. By law an exporter cannot be a whole seller, which makes traceability impossible. But in the old auction system, in which each transaction is auctioned independently, traceability was made possible by using extended families as whole sellers, processors and even farmers. In auction time the exporter will buy and sell his/her-own coffee at whatever price, to be in line with legal requirement (see Eleni et al, 2003 and Eleni et al, 2006). But when commodity exchange introduced warehouse receipt system with clearly defined grade and standard, all similar grade coffee are pulled together as result such loophole was not possible (*Molina, 2010*). Even though market for speciality coffee is introduced later (Eleni, 2012) still it will not address the traceability problem. This is serious problem that needs to be addressed (*Molina, 2010*).

The other problem is questionable independence of the commodity exchange management from the politics of the time. There was heavy handed government direct intervention. In this period assuming that coffee exporters are hording coffee for speculation purpose, there was heavy government intervention on both exporters business (storage) and actually trading using state enterprise, which includes the termination of export license for the dominant traders, nationalization of their coffee and involvement of state enterprises and quasi private (quasi public) enterprises in coffee trading and export (Molina, 2010).

Commodity exchange is highly debatable institution in Ethiopia. By some it is seen as the reflection of the country bright future and by others as another means of government control and homogony (see Eleni, 2012). However there does not seem to be adequate study done to understand the performance of commodity exchange. In this paper AFRIMA(p, q)-M-HYGARCH(q, p) model will be used to understand the data generating process of temporal profit of whole sellers with in commodity exchange.

Theoretical and empirical back ground

In developing economies where market failures are very serious commodity exchange is defined as integrated solution to most market failures (Eleni and Goggin , 2005 and Taddese and Fikadu, 2010). By integrating commodity exchange with warehouse receipt system that allows for discounted loan and receipt based trading, search cost can be reduced, storage problem and flexible access to loan can be made possible (Taddese and Fikadu, 2010). The open outcry or electronic based trading will make price discovery transparent and competitive (ibid). Moreover experimental studies did clearly show that the double auction system which is used with in commodity exchange is more efficient way of price discovery (Smith and Williams, 1990).

Option and future trading could also facilitate efficient management of risk by transferring risk from the most risk averse to the less risk averse for price. (UNCTAD, 1998). Moreover centralized information collection, forecasting and dissemination could be also made possible in economic manner given information is none rival in nature (Taddese and Fikadu, 2010). So to accept commodity exchange as an integrated solution for most market failures seems logical, especially if the necessarily regulatory frameworks are in place.

The problem is that empirical result show that experiments in developing commodity exchange in the last 20 to 40 years was not very successful in less developed economies (Santana-Boado and Brading, 2000). It is true the most successful commodity exchanges in the same period are not found in developed economies but in developing middle income economies like China (Rutten, 2005). But the success in less developing economies is not satisfactory.

The problem with commodity exchange is that not only commodity exchange will solve market failures but also it works well when market failures are not serious. (Lovelace 1998, UNCATD, 2005 and UNCTAD and WB, 1993). For effectiveness capacity to trade on large volume is needed to reduce average variable cost, a minimum flow of output is needed to reduce sunk or fixed cost, a highly functional telecommunication and financial sector is needed to make the marketing system efficient and the market highly liquid (Taddese and Fikadu, 2010). Such conditions are less satisfied in less developed economies compared to middle income countries. This is chicken and egg problem that commodity exchange is needed to solve market failures but again as market failure increase commodity exchange is highly ineffective. This vicious cycle can be easily broken, if there is dynamic, adaptive and flexible management. What is needed is a dynamic and independent management that can identify ever changing challenges and who can find effective solutions (Taddese, 2006).

So the performance of any commodity exchange needs to be carefully studied, especially in less developed economies like Ethiopia. And it is hope of the researcher that studies, like this one, will contribute to better understanding of commodity exchange and contribute useful knowledge in tailoring the Ethiopian Commodity exchange to Ethiopian reality. Now we will focus on model specification.

AFRIMAX(p, q)-M-HYGARCHX(q, p) model specification

If P_t is price in period t, the continuous temporal profit for whole sellers over one period or one day in this case in period t is given as

$$y_t = \ln(P_t) - \ln(P_{t-1}) \qquad (1)$$

Following the conventional time series data generating process this can be represented in auto regressive moving average representation with auto regressive order of p and moving average order q or $ARMA(p,q)$. Formally

$$y_t = \mu + \sum_{i=1}^{p} \alpha_i y_{t-p} + \sum_{j=1}^{q} \beta_j v_{t-j} + v_t \qquad (2)$$

Using the conventional lag operators we can represent it in the following form

$$\phi(L) y_t = \mu + \Phi(L) v_{t-j} + v_t \qquad (3)$$

Where $\phi(L) = 1 - \sum_{i=1}^{p} \alpha_i L^i$ and $\Phi(L) = 1 + \sum_{j=1}^{q} \beta_j L^j$

To check stationary nature of the data or to check for unit root, we have to factor out one lag

$$\phi(L)^* [1-L] y_t = \mu + \Phi(L) v_{t-j} + v_t \qquad (4)$$

Where $\phi(L) = \phi(L)^* [1-L]$ and assuming all lags in $\phi(L)^*$ are having roots greater than one, if the root of $[1-L]$ is greater than one $\phi(L)$ it is stationary and $\phi(L)$ is invertible. So we can apply the normal stationary time series assumptions in y_t. In this case there is no need to factor $[1-L]$ out or it can be represented as $\phi(L) = \phi(L)[1-L]^0 = \phi(L)$.

$$y_t = [\phi(L)]^{-1} \mu + [\phi(L)]^{-1} \Phi(L) v_{t-j} + [\phi(L)]^{-1} v_t \qquad (5)$$

This is stationary $ARMA(p,q)$ model. If $[1-L]$ is having unit root or root less than zero or Eigen value greater than one, we can only invert it in first difference

$$[1-L] y_t = dy_t = \left[\phi(L)^*\right]^{-1} \mu + \left[\phi(L)^*\right]^{-1} \Phi(L) v_{t-j} + \left[\phi(L)^*\right]^{-1} v_t \qquad (7)$$

As can we see it above $[1-L]^1$ is used when the data is having unit root and $[1-L]^0$ is used when the data is stationary. We can generalize it in to $[1-L]^d$ as developed by Granger (1980, 1981), Granger and Joyeux (1980) and Hosking (1981).

$$\phi(L)^* [1-L]^d y_t = \mu + \Phi(L) v_{t-j} + v_t$$

$$\left[1-L\right]^{d} y_t = \frac{\mu}{\phi(L)^*} + \frac{\Phi(L)v_{t-j}}{\phi(L)^*} + \frac{v_t}{\phi(L)^*} = ARFIMA(p,d,q)$$ 8

Equation 8 is Auto regressive, fractionally integrated, moving average (ARFIMA) model for d taking any real number as value. If -0.5 < d < 0.5 it is invertible and stationary, means we can apply the normal time series property. If d ≥ 0.5 we have unit root (d= 1 being one example) and if d ≤ -0.5 it is not invertible but still stationary. The advantage of frictionally integrated function than the normal integration at integer level is that first it allows for slow decay of memory or persistence of shocks with hyperbolic decay than the fast geometric (exponential) decay imposed by ARCH terms. If d ≤ 0, the market has short memory as represented by the auto regressive terms but if d ≥ 0 the market has long memory of distant past realizations. Second it generalizes both integration and unit root by using any real number representing the order integration. Most importantly, if linear combination of two or more variables generates integration order below the order of the level data, it will show cointegration. Means the jump is not from unit root (d = 1) to stationary with d = 0, but any reduction in d say from 0.5 to 0.4 will show cointegration (Granger, 1981).

If we assume the error term in the above equations or $[v]$ is independently and identically distributed error term, it will be the end of the story but if there is ARCH or GARCH effect in the model, we need to take that in to account. If there is ARCH (Engle, 1982) or GARCH (Bollerslev, 1986) effect, $v_t = \sigma_t \varepsilon_t$ will hold. The real error term is defined as ε and is independently and identically distributed error term. Equation 8 will become as given in equation 9, below, and there is time varying heteroskedasticity.

$$\left[1-L\right]^{d} y_t = \frac{\mu}{\phi(L)^*} + \frac{\Phi(L)v_{t-j}}{\phi(L)^*} + \frac{\sigma_t \varepsilon_t}{\phi(L)^*}$$ 9

The generalized auto regressive conditional heteroskedasticity model of auto regressive order of q and moving average order of p or $GARCH(q,p)$, of Bollerslev (1986) which is a generalization of a path breaking work of Engle (1982), given $E\left(v_t^2\right) = \sigma_t^2$, can be presented as following

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i v_{t-q}^2 + \sum_{i=1}^{p} \beta_{i-p} \sigma_{t-p}^2$$ 10

If we add $u_t = v_t^2 - \sigma_t^2 = \varepsilon_t^2 \sigma_t^2 - \sigma_t^2 = \left(\varepsilon_t^2 - 1\right)\sigma_t^2$ to both sides, we will get

$$v_t^2 = \omega + \sum_{i=1}^{q} \alpha_i v_{t-q}^2 + \sum_{i=1}^{p} \beta_{i-p} \sigma_{t-p}^2 + u_t$$ 11

Using conventional lag operators we can represent equation 11 as following

$$\phi(L)v_t^2 = \omega + \Phi(L)\sigma_\varepsilon^2 + u_t \qquad \text{.......12}$$

Following Davidson (2004) we can present it as frictionally integrated generalized auto regressive conditional heteroskedasticity model with hyperbolic memory (HYGARCH)

$$\phi(L)^*\left[1+\alpha\left[(1-L)^d - 1\right]\right]v_t^2 = \omega + \Phi(L)\sigma_\varepsilon^2 + u_t \qquad \text{.......13}$$

Assuming that all roots in $\phi(L)^*$ have Eigen value less than one or roots greater than one we can represent it as

$$\left[1+\alpha\left[(1-L)^d - 1\right]\right]v_t^2 = \left[\phi(L)^*\right]^{-1}\omega + \left[\phi(L)^*\right]^{-1}\Phi(L)\sigma_\varepsilon^2 + \left[\phi(L)^*\right]^{-1}u_t \qquad \text{.......14}$$

If α is equal to 1 then we have FIGARCH model of BBM (Baillie, Bollerslev and Mikkelsen, 1996) or Chung (1999). Moreover if α is equal to 1 or log(α) is equal to 0, it also implies FIGARCH model is appropriate (Davidson, 2004). If the above conditions hold, equation 14 will become

$$(1-L)^d v_t^2 = \left[\phi(L)^*\right]^{-1}\omega + \left[\phi(L)^*\right]^{-1}\Phi(L)\sigma_\varepsilon^2 + \left[\phi(L)^*\right]^{-1}u_t \qquad \text{.......15}$$

The basic difference between BBM and Chung version of the model is in the estimation of the constant term. What Chung did is that in equation 10, σ^2 is subtracted from both sides to get

$$\left[v_t^2 - \sigma^2\right] = \left[\omega - \sigma^2\right] + \sum_{i=1}^{q}\alpha_i v_{t-q}^2 + \sum_{i=1}^{p}\beta_{i-p}\sigma_{t-p}^2 + u_t \qquad \text{.......16}$$

And following the logic of equations from 12 to 15 we will get

$$(1-L)^d\left[v_t^2 - \sigma^2\right] = \left[\phi(L)^*\right]^{-1}\left[\omega - \sigma^2\right] + \left[\phi(L)^*\right]^{-1}\Phi(L)\sigma_\varepsilon^2 + \left[\phi(L)^*\right]^{-1}u_t \qquad \text{.......17}$$

This will allow efficient estimation of the constant as approximately equal to zero without depending on initial value on the maximum likelihood optimization process. This adjustment is also applied in estimation of the HYGARCH model of Davidson too, as it allow for more independent estimation of the constant from initial values in the estimation process. If $d = 0$ holds, all roots in $\phi(L)$ are having roots greater than 1 or Eigen value less than one, so we have

$$v_t^2 = \left[\phi(L)\right]^{-1}\omega + \left[\phi(L)\right]^{-1}\Phi(L)\sigma_\varepsilon^2 + \left[\phi(L)\right]^{-1}u_t \qquad \text{.......18}$$

This is the conventional GARCH model of Bollerslev (1986). If we impose $\Phi(L)+\phi(L)=1$, then we have IGARCH model of Engle and Bollerslev (1986) as sited in Engle and Bollerslev (1993) and what we actually estimate is $\phi(L)$ and $\Phi(L)$ is derived by using $\Phi(L)=1-\phi(L)$. Note that in equation 14, if α is equal to zero, we also have stable GARCH model. Once we define how to estimate the conditional variance or σ_t^2, we can combine the AFRIMA (p, q) estimation and HYGARCH estimation (to represent all of them). Given equation 1 and using the fact $\sigma_t\varepsilon_t = v_t$, we will have

$$y_t = \mu + \sum_{i=1}^{p}\alpha_i y_{t-p} + \sum_{j=1}^{q}\beta_j v_{t-j} + \sigma_t\varepsilon_t \quad \text{...19}$$

And using the conditional standard deviation as weight, we have

$$\frac{y_t}{\sigma_t} = \frac{\mu}{\sigma_t} + \sum_{i=1}^{p}\alpha_i \frac{y_{t-p}}{\sigma_t} + \sum_{j=1}^{q}\beta_j \frac{v_{t-j}}{\sigma_t} + \varepsilon_t \; .$$

$$\frac{y_t}{\sigma_t} = \frac{\mu}{\sigma_t} + \sum_{i=1}^{p}\alpha_i \frac{y_{t-p}}{\sigma_t} + \sum_{j=1}^{q}\beta_j \varepsilon_{t-j} + \varepsilon_t \quad \text{...20}$$

This will give us a combined model of AFRIMA (p, q) and HYGARCH (q, p) and notice ε is independently and identically distributed but can follow either normal, student, skewed student, GED distribution and soon. The most parsimonious distribution for the data used in this paper is selected based on information criterions. Following the initial work of Engle, Lilien and Robins (1987) we can also allow the conditional variance to effect return, representing risk premium.

$$\frac{y_t}{\sigma_t} = \frac{\mu}{\sigma_t} + \sum_{i=1}^{p}\alpha_i \frac{y_{t-p}}{\sigma_t} + \sum_{j=1}^{q}\beta_j \varepsilon_{t-j} + \delta\sigma_t^2 + \varepsilon \quad \text{..21}$$

This is AFRIMA (p, q)-M-HYGARCH (q, p) model. Where δ is representing temporal risk premium to sellers in this model. Before we end this part it is important to notice that the interpretation of d_AFRIMA is different from interpretation of $d\_HYGARCH$ or $d\_FIGARCH$ (Davidson, 2004). So if $d\_HYGARCH$ or $d\_FIGARCH$ approaches zero or one we have short memory but as they depart from 0 to positive side without approaching 1, the market has longer memory of shocks to conditional variance. The next focus is specification of a test for leverage effect or signed bias test in volatility following Engle and Ng (1993). Let use the error terms in equation 1 and 11 or v_t and u_t

$$v_t^2 = a + \theta S^- + \gamma S^- u_{t-1} + \rho S^+ u_{t-1} + e \quad \text{.........................22}$$

The variable S^- is dummy variable having value of 1 when u_{t-1} is negative and Zero otherwise. And S^+ is dummy variable associated with positive values of u_{t-1}. The statistical significance of θ, γ and ρ will measure sign bias, negative sign bias and positive sign bias, respectively, with null there is no bias. The overall bias statistics is LM statistics equal to $T \times R^2$ and it follows chi-square distribution with three degree of freedom. Where T is number of observation in equation 22 and R^2 is its degree of determination. Given this fact let's focus on the empirical result next.

Description of the data

The data used in this paper covers from December 2, 2008 (the first day of trading coffee) to august 10, 2010. It is daily price data for washed coffee that is destined for export. In Ethiopia high quality coffee cannot be distributed to domestic economy, so it is explicitly destined for export (Federal Negarit Gazeta, 2008). This is high frequency but also limited size data representing 399 trading days, spanned in three years.

Table 1 descriptive statistics

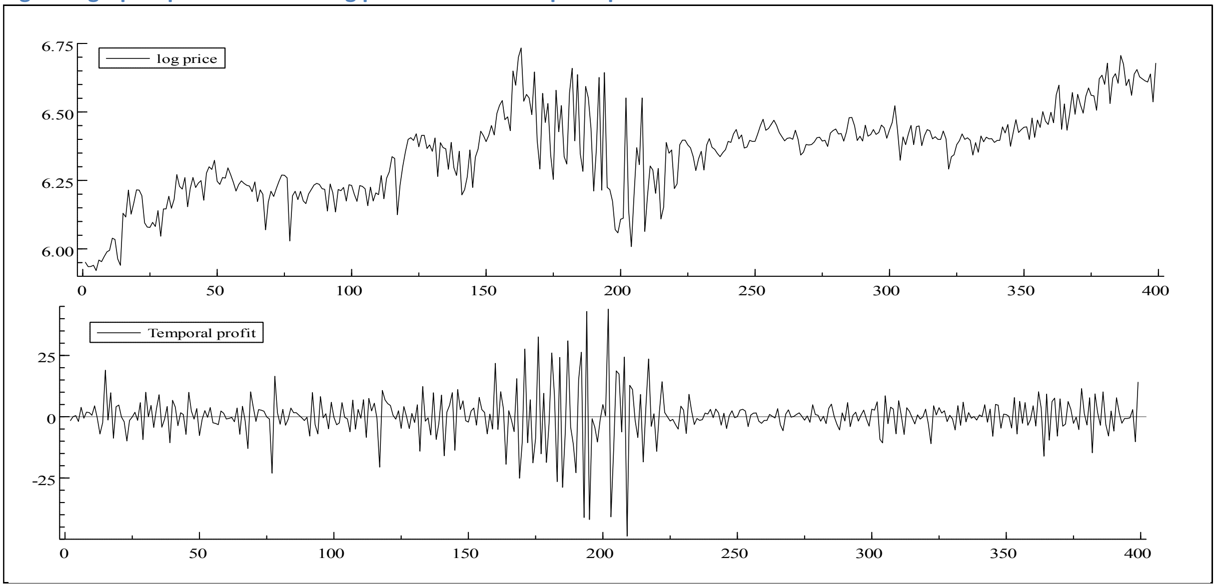
Variable	min	mean	max	std.dev
Log price	5.9209	6.3481	6.7334	0.15882
temporal profit	-48.729	0.1826	43.913	9.3836

As we can see it, in table 1 above, temporal profit is highly dispersed compared to log price. And table 2 below show that the level data (log price) is normally distributed with minor negative skewness, but the first difference (temporal profit) is far from normal with significant negative skewness but highly significant excess kurtosis. The first difference is far from following normal distribution and the existence of excess kurtosis is first indicator of ARCH/GARCH effect.

Table 2 descriptive statistics of the density function

log price	Statistic	t-Test	P-Value
Skewness	-0.22328	1.8253	0.067952
Excess Kurtosis	-0.049994	0.20486	0.83769
Jarque-Bera	3.3484	.NaN	0.18746
Temporal profit	Statistic	t-Test	P-Value
Skewness	-0.32882	2.6881	0.007186
Excess Kurtosis	6.9706	28.563	1.95E-179
Jarque-Bera	812.93	.NaN	2.98E-177

Figure 1 graphic presentation of log price data and temporal profit



As can be seen from figure 1 above, the level of log price data shows none stationary pattern while the first difference is mean preserving stationary process, with high cluster of volatility especially in trading days spanned from around 160 to 225. This is clear indicator Volatility cluster has to be modelled in first difference than level data. Formal test for Arch/GARCH effect and serial correlation is done and given in table 3, below.

Table 3 Test for ARCH/GARCH effect and serial correlation in level data

Temporal profit ARCH test	Statistic	P-Value
ARCH 1-2 test: F(2,393)	57.111	0.0000
ARCH 1-5 test: F(5,387)	23.687	0.0000
ARCH 1-10 test: F(10,377)	19.978	0.0000
Q test on Raw data of temporal profit		
Q(5)	100.647	0.0000000
Q(10)	161.516	0.0000000
Q(20)	222.214	0.0000000
Q(50)	298.159	0.0000000
Q test on squared raw data of temporal profit		
Q(5)	155.078	0.0000000
Q(10)	425.038	0.0000000
Q(20)	660.488	0.0000000
Q(50)	755.463	0.0000000

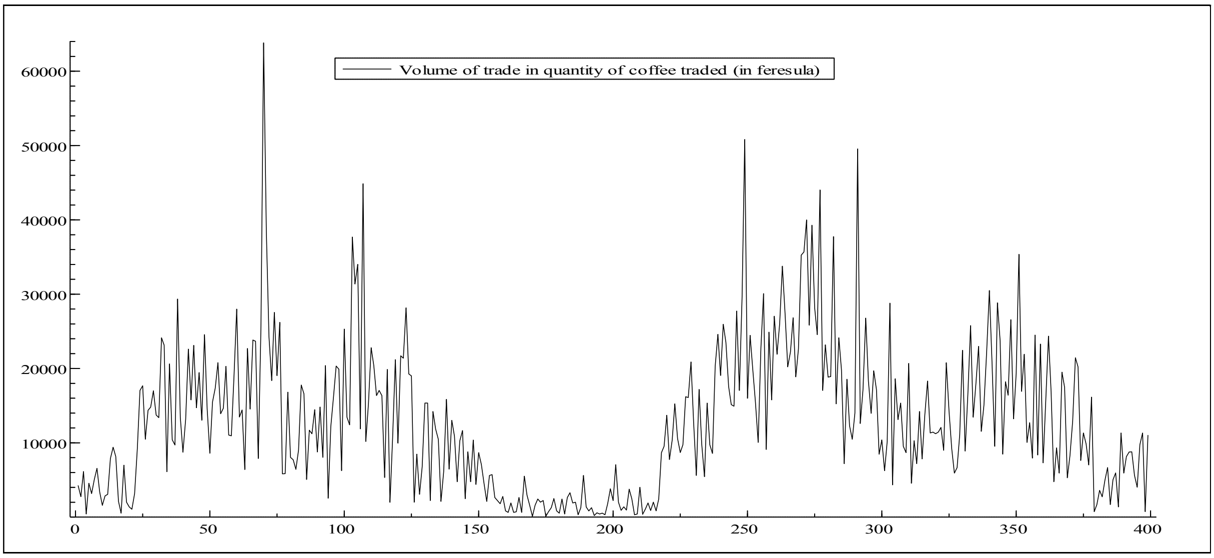
Given the existence of serial correlation we cannot take the above result as final indicator for existence of ARCH/GARCH effect but it is clearly shows there is high chance that there is cluster of volatility in first difference or temporal profit data. Moreover when the model is fitted to the entire data set it was not possible to find a single ARFIMA-HYGARCH specification (or its special cases) to describe the data. The problem seems the data generating process was changed around August 2009 to November 2009.

Table 4 descriptive statistics by year and month

year	2008		2009		2010	
Month	mean	std.	mean	std.	mean	std.
January			0.002309	0.059353	-0.00206	0.025178
February			-0.00142	0.039555	0.005062	0.023232
March			-0.00111	0.08031	-0.00312	0.049727
April			-0.00174	0.044608	0.000753	0.039314
May			0.010031	0.075106	0.002044	0.039291
June			-0.00627	0.070604	0.0041	0.070198
July			0.01511	0.085599	0.004659	0.065181
August			0.003813	**0.184816**	0.008241	0.078532
September			-0.03743	**0.292527**		
October			0.004879	**0.229062**		
November			0.004418	**0.103432**		
December	0.013184	0.058193	0.001027	0.035581		

As we can see it in table 4 above the variability from August 2009 to November 2009 was exceptionally high. If we see the standard deviation in August 2010 and compare it with August 2009, we see that August 2009 was exceptionally very volatile.

Figure 2 Volume of trade in Feresula



Moreover as we can see it in figure 2 above the volume of trade in this period is exceptionally very low. A study by Elien et al (2003) did show that pick period is in December to February and the rainy season, which is related to the volatile months, are the lean season. However the same level of extreme declining trend is not observed in the last days of the data (around 400) which is related to August of 2010. There is possible seasonality in the data that we are not able to check given limitation of the data.

This period is also related to policy related instability. Where government facing ever increase coffee prices and shortage of foreign exchange was accusing exporters of speculation on prices. Direct actions were taken by the state to regulate the market, nationalize stored coffee of dominant exporters and direct export of coffee using state enterprises (Molina, 2010). The problem is started with public condemnation of manipulative exporters by the prime minster. This is followed by nationalization of the stored coffee of the dominant exporters (Bloomberg, 2009) and suspension of their export license in March 2009 (The New York Times, 2009). Then Guna, an endowment company established by the ruling party, and Ethiopian Grain Trade Enterprise (EGTE), state owned enterprise, start to engage in coffee export in April 2009 (Addis Neger, 2010 and Comtex, 2009). There was heavy socio political upheaval in this time (see Elien, 2012). But this was mostly done until end of April. But the shock seem to happen in August, means after 2 to 3 months.

This would make the structural break unrelated to the policy but a study by Elien et al (2003) did show that since future trading is not possible but exporters have to enter 2 to 3 months future contract in international coffee markets and given final processing of coffee is done by exporters and this needs time; the effect of the policy would be observed with lag which could extend 2 to 3 months. This is more the case if exporters have habit of storing coffee, when they are in short position in international coffee market, than taking the price risk in future spot market price. Actually, exporters do have tendency to store coffee and this is the most important reason for their dispute with the state. Since the dominant traders are excluded and the least dominant traders may store only up to 2 to 3 months to cover their future contract and may export whatever they have to avoid conflict with state, the effect of policy could be observed after 2 to 3 months, when new future contracts have to be signed. However given the limitation of the data, we are not able to exclude the effect of seasonality and many assumptions are done in linking the policy with the change. So these facts should be taken in to account, in the following analysis.

However there is news evidence to back above assumption first the problem did persist at least until April 29, 2011 given a letter written by Ministry of Trade and Industry in April 29, 2011, to coffee exporters association insist that hording by exporters is negatively effecting the country's export revenue and export business and state administrative actions that could be taken if such practice continuous (Bloomberg, 2011). And the response of a trader as cited in Bloomberg is presented as following

> *"The regulation is not 'workable' because exporters have legitimate reasons to contravene it, said Fekade Mamo, a board member of the exchange and chief executive officer of Mochaland Import export PLC, a closely held coffee exporter. The process of delivering samples to buyers before a contract is signed may take more than two months and a "good" exporter would want to hold as much as 1000 tons in stock ready to deliver, he said by phone on may 9 from Addis Ababa, the capital."*

Means if there is need to store coffee for two months or more, the effect of change will be observed after few months of lag. It is clear the data generating process in this period was not the same as before. That is why in this study the data is divided in to three periods. The first period represents from December 2008 to July 2009, the second period represents from August 2009 to November 2009 and the final period represents December 2009 to August 2010. This approach have high cost but also some important benefits. The cost is the limitation in data it creates. For this kind of analysis large data set is needed especially if the data is not normally distributed. The initial 399 observation was not adequate and the division in to three groups will create much smaller samples. But to counter this problem, the models are checked by imposing different distributions. The distribution used are normal, student t, skewed student and GED. This will help us to see if the result is sensitive to distributional assumption imposed. The advantage is we can compare those volatile periods, with heavy hand of the state, with both initial period and post volatile periods. This will give us important information about the effect of state policy in this period.

Pattern of export washed coffee temporal profit with in Ethiopian commodity exchange in pre volatile months (pre 166^{th} trading day)

The models given below, for all periods, are selected by Schwarz information criterion given there is no serial correlation. Different distributions are used for error term and the one presented here is the one selected based on information criterion. But the result of all other distributions is given in appendix 1. Given this fact let's focus on the result given in table 5, below.

In pre summer shock of 2009 which is observed to create structural break in the temporal profit, the market is observed to have very short memory of temporal profit around the average daily profit of 0.2 to 0.35%. Means any shock to profit will die very fast and the market does stabilize itself to trend of price increase in range of 0.2 to 0.35% per day. This is so since the d-Arfima term in all models is less than 0 and very close to -0.5. This clearly shows that the price determination was efficient, if measured by traders being price takers and cannot use past information to extract extra profit.

Table 5 ARCH/GARCH type of model for pre 166 trading day, based on skewed student distribution

HYGARCH			
Variable	Coefficient	Std.Error	Nyblom[1]
Cst (M)	0.207745	0.13739	0.28393
d-Arfima	-0.31101***	0.094833	0.08695
AR(1)	-0.177198	0.1101	0.05944
d-Figarch	0.206631	0.2598	0.4464
ARCH (Phi1)	0	0.37571	0.10902
Asymmetry	-0.364707**	0.15431	0.15858
Tail	3.055444***	1.138	0.52864
Log Alpha (HY)	0.805421	0.81703	0.49749
FIGARCH- CHUNG			
Variable	Coefficient	Std.Error	Nyblom
Cst (M)	0.297124***	0.068929	0.30864
d-Arfima	-0.420386***	0.060934	0.1011
Cst (V)	41.844784***	15.548	0.38457
d-Figarch	0.177878*	0.10032	0.12561
Asymmetry	-0.26779**	0.13227	0.20387
Tail	4.071776***	0.96835	0.49331
FIGARCH –BBR			
Variable	Coefficient	Std.Error	Nyblom
Cst (M)	0.297124***	0.068929	0.30864
d-Arfima	-0.420386***	0.060934	0.1011
Cst (V)	41.844784***	15.548	0.38457
d-Figarch	0.177878*	0.10032	0.12561
Asymmetry	-0.26779**	0.13227	0.20387
Tail	4.071776***	0.96835	0.49331
GARCH			
Variable	Coefficient	Std.Error	Nyblom
Cst (M)	0.355646***	0.064288	0.26482
d-Arfima	-0.431259***	0.057058	0.10966
Cst (V)	37.045004***	8.6935	0.66403
Asymmetry	-0.171447	0.10624	0.17099
Tail	3.804166***	1.0152	0.57793
IGARCH			
Variable	Coefficient	Std.Error	Nyblom
Cst (M)	0.244011***	0.057599	0.36447
d-Arfima	-0.428725***	0.056444	0.10215
Cst (V)	9.424733*	4.9968	0.35102
ARCH (Phi1)	0.393433***	0.11523	0.34563
GARCH(Beta1)	0.606567		
Asymmetry	-0.338974***	0.12006	0.21284
Tail	3.067447***	0.55621	0.42737

Note 1 * significant at 10%, ** significant at 5% and *** significant at 1%

[1] Asymptotic 1% critical value for individual Nyblom statistics = 0.75.
Asymptotic 5% critical value for individual Nyblom statistics = 0.47.

The d-Figarch terms ranges from 0.177878 to 0.206631, but are insignificant at conventional 5% level. This shows us the market has short memory of shock to variance. Means the effect of random increase in variance will not persist for long period to make the market very unstable. But In FIGACH models the value is significantly different from zero at 10% and if we take the t value for d-Figarch = 1, it is 8.19, which is significant at 1%. This shows there is possibility for some persistence of shocks.

All the models, except one, show that in this period there was no evidence for any volatility cluster or ARCH/GARCH effect. All models do find excess kurtosis, which is an indicator of ARCH/GARCH effect, though ARCH/GARCH effects are not the only source of fat tails. In terms of asymmetry the result shows that extreme losses are more probable to happen than extreme gains. The negative skewness is significant but small in magnitude though and is unstable at 5% level.

The result of HYGRCH model is not good fit to the data given Log Alpha is zero and as result alpha is one, showing the appropriate model is FIGARCH not HYGARCH. This model also has some stability problem in tail, d-figarch and log alpha parameters. Farther more d-Figarch is also zero, which shows even FIGARCH models are not right. It is better to test this result from FIGARCH models than from more restrictive and general HYGRCH model. If we focus on FIGARCH models we see that the market is highly volatile but the volatility is not behind bound. If we focus on constant in the variance equation, we see it is very big reflecting most of the variability in profit is not structural, clustered or inertia but just the market is volatile in nature, without any complex structure of volatility. There is some form of volatility persistence as d-Figarch term is significant at 10% but not at lower levels. Means the market is highly volatile without any clustered structure but when shocks happen there is tendency for the effect of the shock to variance to persist. But the persistence is insignificant at 5% but just 10%. The next logical model is simple GARCH. GARCH did not show any change but to reduce the constant variance in profit from 41 to 35, but the market is still without any volatility cluster. However the estimate of the estimate of constant in variance equation becomes unstable.

If we use IGRACH model by imposing that Phi1 + Beta1 = 1, means if we demand not only ARCH/GARCH effect but if we also impose that Beta1 = 1- Phi1 must hold, the model shows us that there is significant cluster of volatility where 39.3% of one period lagged variance will persistence to current period and profit variability from long period do effect current profit variability with geometric scale. Means recent variability will have more effect but the effect will decay at geometric scale as the time lag increase. The cumulative effect on current variability is close to 61%. This shows that the market cannot easily digest shocks to variability and as result there is no limit to what level of shock could happen as Phi1 + Beta1 = 1 and unconditional variance does not exist. The constant variance now declines to just less than 9.5 and is stable.

So the models have some form of memory which can be represented either in Geometric decay of IGARCH or less significant hyperopic decay. Since in GARCH model the condition for IGARCH is not holding, it is more logical the models are finding it hard to select from low memory and very long memory given the sample size. So let's check for information criterion to select the most parsimonious model.

Table 6 Information criterion for different ARCH/GARCH type of model with skewed student distribution pre shock

Model	HYGARCH	FIGARCH- CHUNG	FIGARCH -BBR	GARCH	IGARCH
Log Likelihood	**-506.287**	-508.956	-508.956	-510.956	-506.788
Akaike	6.271795	6.279945	6.279945	6.292151	**6.253506**
Schwarz	6.423008	6.393355	6.393355	6.386659	**6.366916**
Shibata	6.267325	6.277392	6.277392	6.290365	**6.250953**
Hannan-Quinn	6.333182	6.325985	6.325985	6.330518	**6.299546**

The above table shows us that IGARCH is the most parsimonious model. In addition, the fact that the constant in GARCH model is not stable, at 5% but just 1%, does tale us that it is not good representation. FIGARCH and IGARCH did make it stable. However we also observe the D-figarch term is significantly different from 1 but only at 10% it is different from zero. The logical implication is that: there is some insignificant long memory which can be parsimoniously represented by IGARCH model with short memory, given the limitation of the data size (164 data points representing 165 first days of trading). But it is more appropriate to assume the data shows some intermediate memory.

Moreover when different distributions are used than skewed student distribution (see appendix 1) there seems to be evidence for strong GARCH (Beta1) effect (close to 1) and close to zero ARCH (Phi1) effect. Means the market have high chance of being explosive depending on historical variability given volatility cluster, without being dependent on short term volatility. Since GARCH (Beta1) will allow for geometric decay of memory over infinitive time and is middle point between Hyperbolic memory represented by D-figarch and very short memory represented ARCH (Phi1), it will satisfy the above conclusion. More over even though skewed student distribution is selected based on information criterion the estimate of the tale is unstable except in IGARCH. This shows us that distribution does matter and skewed t-distribution may not be the best in this data set. If we accept there is IGARCH data generating process unconditional variance does not exist and the conditional variance should be understood as predicted volatility than conditional variance per se.

Table 7 Test for ARCH/GARCH affect pre shock

Test type	Q test on standardized error for serial		Q test on squared error for GARCH		Residual Based test for GARCH			F test for ARCH			
TEST	VALUE	PROB.	VALUE	PROB.	TEST	VALUE	PROB.	TEST	DF	VALUE	PROB.
Q(5)	3.304	0.653	0.289	0.998	RBD(2)	0.202	0.904	ARCH 1-2	2, 149	0.08	0.92
Q(10)	6.957	0.73	8.261	0.603	RBD(5)	0.309	0.997	ARCH 1-5	5, 143	0.059	1
Q(20)	12.493	0.898	11.549	0.931	RBD(10	-0.069	1	ARCH 1-10	10,	0.713	0.71
Q(50)	38.784	0.875	34.323	0.956							

However ARCH/GARCH test done on the profit equation shows that there is no evidence for any ARCH/GARCH effect in the data, see table 7 above. So it is logical to accept the fact that at this period the existence of volatility cluster is not very significant though the market was highly volatile. In table 8, below, specification tests are given for different models used within skewed student distribution.

Table 8 Tests for ARCH/GARCH type of model with skewed student distribution in pre shock (1 – 155 day of trading)

TEST Type		HYGARCH		FIGARCH-		FIGARCH -BBR		GARCH		IGARCH	
Q test standardized	TEST	VALUE	PROB.	VALUE	PROB.	VALUE	PROB.	VALUE	PROB.	VALUE	PROB.
	Q(5)	0.923	0.921	2.699	0.746	2.7	0.75	2.4	0.791	3.005	0.699
	Q(10)	3.832	0.922	6.493	0.772	6.49	0.77	6.278	0.791	6.868	0.738
	Q(20)	8.116	0.985	10.277	0.963	10.28	0.96	10.144	0.965	10.882	0.949
	Q(50)	44.094	0.672	42.063	0.78	42.06	0.78	38.001	0.893	43.249	0.739
Q test on squared	Q(5)	1.382	0.847	1.109	0.953	1.109	0.953	1.547	0.908	1.501	0.682
	Q(10)	9.837	0.364	7.914	0.637	7.914	0.637	7.267	0.7	7.718	0.461
	Q(20)	12.334	0.871	11.653	0.928	11.653	0.928	12.742	0.888	11	0.894
	Q(50)	32.366	0.968	35.425	0.941	35.425	0.941	36.899	0.916	27.914	0.991
Residual Based test	RBD(2)	-	1	0.561	0.755	0.561	0.755	0.637	0.727	3.433	0.18
	RBD(5)	-1.063	1	0.648	0.986	0.648	0.986	0.764	0.979	7.214	0.205
	RBD(10)	15.265	0.123	-1.449	1	-1.449	1	5.533	0.853	10.8	0.373

Both models (ARFIMA and HYGARCH) point toward few common facts: First it will not possible to predict future price and temporal profit moments by using past profits and prices. Measured from this angle the market was efficient. Second the market has intermediate memory of random shocks to variance with recent shocks having more impact but the existence of such geometric memory is questionable given the limitation of the data. Third all models do show high variability problem in prices and profit. The difference comes in the nature of the variability. Most models show that the market is just unpredictable but there is no complex structure behind it. IGARCH model show that most of the variability is caused because shocks will come in cluster and actually there is no limit to the level of variability that could be observed from one day to another, given unconditional variance does not exist which can limit maximum size of the conditional variance. So at initial 155 days of trading the market was volatile but neither return nor variability was predictable. Relatively however variability was more predictable than return. But variability itself is very hard to predict since random shocks can easily dominate the long (intermediate) memory. Means the market is not efficient in handling risk but relatively efficient since price manipulation is not possible or nobody can extract information from past history to extract extra profit. Now let's focus on the highly unstable period between 166 to 249 day of trading (August 2009 to September 2010), where the raw data shows high level of instability and structural break.

Pattern of export washed coffee temporal profit with in Ethiopian commodity exchange in volatile months (166 to 249 day of trading)

In this period which accounts for summer of 2009 or specifically from early August to end of September where the market is highly volatile, the market structure is clearly changed as we can see it from the result given in table 9 below. But before we go to analysis, it is important to remember the data covers 84 trading days only and the result should be taken with great reservation or similar study have to done in very low frequency data say price of a single contract, before it can be accepted as fact.

Focusing on profit it is observed that the best fit is without constant, showing that on average price change was expected to be zero at this period. Or in other words negative changes of equal magnitude were as probable as positive changes. Moreover it is observed in the data to avoid serial correlation d-Arfima variable, which is significant, coupled with 4 AR terms, which are insignificant, or 5 AR terms, in which the first 4 only are significant, are found to be needed. However the first one is selected in all models except HYGARCH by information criterion. Given the market has short memory or d-Arfima is -0.56 and given standard error is in range of 0.11 to 0.12, the null hypothesis that d-Arfima is equal to -0.5 against it is greater than -0.5 is rejected at 1% level.

This shows the market is having the low memory of lagged profit but still it is invertible. Moreover it is logical to state that the market will remember profit up to 4 to 5 days to the past but not more than that. Basically the market temporal profit was self stabilizing around zero given it has low memory and negative AR coefficients.

Going to volatility we observe the market clearly did experience structural change in this period. In this period the market start to have short memory of shocks to variance means the effect of random shock to variance in given period will not have lasting effect at hyperbola or slow level of decay. Note that d-figarch is significantly different from zero but not one. Except in BBR, both Chung and HYGARCH predicted it to be one and in BBR the t value, with null that d-figarch = 1, is -0.26 which is insignificant. This shows us the market does not have hyperbola memory but just short memory. Moreover the constant term in variance equation is zero, as the result the conditional variance completely become dependent on the behaviour of agents and structure of the market. This is clear that in this time there is increase on structural instability of the market.

Table 9 ARCH/GARCH type of model for middle period based on normal distribution

HYGARCH			
Variable	Coefficient	Std.Error	Nyblom
AR(1)	-0.688801***	0.12347	0.22402
AR(2)	-0.6102***	0.14089	0.07539
AR(3)	-0.483689***	0.1448	0.07858
AR(4)	-0.428077***	0.1166	0.02007
AR(5)	-0.11645	0.10601	0.37597
d-Figarch	1***	0.10936	0.11195
ARCH(Phi1)	0	0.24182	0.1733
GARCH(Beta1)	0.76394***	0.12562	0.17593
Log Alpha (HY)	0.003088	0.039565	0.57458
FIGARCH- CHUNG			
Variable	Coefficient	Std.Error	Nyblom
d-Arfima	-0.561249***	0.12529	0.12501
AR(1)	-0.1597	0.14194	0.06943
AR(2)	-0.19228	0.12721	0.23727
AR(3)	-0.07754	0.11722	0.04612
AR(4)	-0.159732*	0.091769	0.07242
d-Figarch	1***	0.051456	0.03381
GARCH(Beta1)	0.73663***	0.069225	0.09483
FIGARCH –BBR			
Variable	Coefficient	Std.Error	Nyblom
d-Arfima	-0.560279***	0.11881	0.12903
AR(1)	-0.15797	0.13931	0.07155
AR(2)	-0.19713	0.12562	0.2321
AR(3)	-0.08034	0.11697	0.04629
AR(4)	-0.163413*	0.091066	0.07769
d-Figarch	0.987105***	0.050335	0.03585
GARCH(Beta1)	0.718097***	0.07471	0.12991
GARCH			
Variable	Coefficient	Std.Error	Nyblom
d-Arfima	-0.561157***	0.12679	0.12217
AR(1)	-0.16026	0.14231	0.0698
AR(2)	-0.19074	0.13034	0.23004
AR(3)	-0.07793	0.11874	0.04487
AR(4)	-0.159787*	0.092701	0.07183
ARCH(Phi1)	0.254318***	0.063159	0.43973
GARCH(Beta1)	0.740031***	0.04666	0.28119
IGARCH			
Variable	Coefficient	Std.Error	Nyblom
d-Arfima	-0.561298***	0.12473	0.12509
AR(1)	-0.159636	0.14071	0.06954
AR(2)	-0.192264	0.12927	0.2372
AR(3)	-0.077532	0.11766	0.04608
AR(4)	-0.159742*	0.091447	0.07249
ARCH(Phi1)	0.263335***	0.045665	0.09474
GARCH(Beta1)	0.736665		

Note 2 * significant at 10%, ** significant at 5% and *** significant at 1%

Geometric memory of shocks was observed in all models in range of 0.71 to 0.76 as parameter of GARCH (Beta1). Means the market has long memory of shocks and shocks did have lasting impact on the long run conditional variance but they are dominated by recent shocks given they are given more weight on geometric scale which declines fast with lag of time. However there is conflict on the models if the short memory can be represented by ARCH(Phi1) or d-figarch = 1. If we have to model the data with first difference on temporal profit, given alpha and d-Figarch, are equal to 1, or if we have to allow ARCH term in level of temporal profit, is not clear. To improve our understanding and to make logical conclusion, let's follow the models starting from HYGARCH.

Table 10 Information criterion for different ARCH/GARCH type of model with normal distribution in shock time

Model	HYGARCH	FIGARCH- CHUNG	FIGARCH -BBR	GARCH	IGARCH
Log Likelihood	-308.006	-305.877	-305.851	-305.87	**-305.877**
Akaike	7.547754	7.449456	7.448826	7.449295	**7.425647**
Schwarz	7.808199	7.652024	7.651394	7.651863	**7.599277**
Shibata	7.527624	7.43694	7.43631	7.436779	**7.416321**
Hannan-Quinn	7.652451	7.530887	7.530257	7.530725	**7.495444**

HYGARCH is not useful as Log Alpha (HY) is not different from zero and is not stable. In this case FIGRACH models can do better in presenting the data. The IGARCH and the GARCH model show that the market is kind of integrated but both FIGARCH model predict that there is no ARCH (Phi1) effect but just GARCH (Beta1) with memory of shocks which is equal or very close to 1. Based on information criterion, shown in table 10 above, IGARCH is the best fit but still the ARCH (Phi1) term is less stable[2] in both GARCH and IGARCH models. Moreover since FIGARCH can nest both models or at least HYGARCH can nest all and in both cases the significance of ARCH (Phi1) is rejected and d-figarch is different from zero, it is more probable that the market has very short memory of shocks to variance which lasts less than one day. But there is volatility cluster depending all times with geometric decay or given very high weights are given to recent shocks.

Table 11 Test for ARCH/GARCH effect in unstable months

Test type	Q test on standardized error for serial		Q test on squared error for GARCH		Residual Based test for GARCH			F test for ARCH			
TEST	VALUE	PROB.	VALUE	PROB	TEST	VALUE	PRO B	TEST	DF	VALUE	PROB
Q(5)			37.228	0	RBD(2)	-9.029	1	ARCH 1-2	2, 79	2.646	0.08
Q(10)	8.737	0.068	56.124	0	RBD(5)	-19.486	1	ARCH 1-5	5, 73	5.82	0
Q(20)	13.664	0.475	63.009	0	RBD(10)	-6.564	1	ARCH 1-10	10, 63	3.001	0
Q(50)	28.978	0.961	115.741	0							

As we can see it in table 11 above there is GARCH and ARCH effect on ARFIMA model based on Q and F tests, but the residual based test for ARCH/GARCH did reject the existence of such effects. The model is fitted with 6 AR terms to avoid serial correlation and other

[2] See foot note 2 for critical values

specifications are not able to solve serial correlation problem. Even in this one there seems to be serial correlation at lower lag and 10% but not 5% if we follow the Q test.

As can be seen in table 12 below there is no serial correlation or ARCH/GARCH problem remaining in the fitted different versions of ARFIMA-HYGARCH models and this is clear indication that there is ARCH/GARCH problem in the ARFIMA model given above. Moreover as we can see it in the appendix 2, when we change the distribution to other forms, there is no change in any of the above analysis. So it is possible to say the result is not affected by assumption of normal distribution used above.

Table 12 Tests for ARCH/GARCH type of model with normal distribution in shock time (166 - 249 day of trading)

TEST Type		HYGARCH		FIGARCH- CHUNG		FIGARCH -BBR		GARCH		IGARCH	
	TEST	VALUE	PROB.	VALUE	PROB.	VALUE	PROB.	VALUE	PROB.	VALUE	PROB.
Q test on standardized error	Q(5)			0.946	0.331	0.969	0.325	0.951	0.329	0.947	0.331
	Q(10)	6.108	0.296	6.038	0.419	6.032	0.42	6.121	0.41	6.039	0.419
	Q(20)	15.623	0.408	18.888	0.275	19.053	0.266	18.937	0.272	18.889	0.274
	Q(50)	45.539	0.45	50.736	0.292	50.772	0.291	50.859	0.288	50.737	0.292
Q test on squared error	Q(5)	0.367	0.947	1.684	0.794	1.635	0.802	1.734	0.629	1.685	0.64
	Q(10)	5.411	0.713	3.888	0.919	3.769	0.926	3.884	0.867	3.888	0.867
	Q(20)	14.173	0.718	19.792	0.407	20.744	0.351	19.837	0.342	19.796	0.344
	Q(50)	32.584	0.957	54.98	0.259	56.867	0.205	55.288	0.219	54.985	0.227
Residual Based test	RBD(2)	0.047	0.977	0.482	0.786	0.412	0.814	0.674	0.714	0.476	0.788
	RBD(5)	-0.033	1	3.013	0.698	3.557	0.615	6.22	0.285	3.01	0.699
	RBD(10)	1.452	0.999	9.455	0.49	7.341	0.693	-44.642	1	7.74	0.654

In this period price is not expected to change from day to day but the market does have short memory lasting up to 4-5 days. The reaction being to correct the shock to lagged profit. If profit was high the best prediction is to say it will be low in next 5 days. Well informed wholesale trader or exporter can easily predict price dynamics in this time to milk some temporal profit. It is more probable at this time government intervention did not make prices more random walk but predictable and manipulate-able. It the same time the shocks become very structural and clustered. In this period though recent shocks to volatility were most important long lagged volatility was also very important at geometrically decreasing weight. Means short living state interventions would not be effective unless they can persist to some time. This is clear indication that policies followed in the volatile months, which include nationalization assets of 'rent seeking' traders, suspension of exporters' licence and direct state engagement in coffee trade were not effective, actually it changed the market structure for the worst. Now let's focus on the last phase of the study time, from trading day 250 to 399 representing 150 trading days. In this period again the market become more stable.

Pattern of export washed coffee temporal profit with in Ethiopian commodity exchange in post volatile months (250 to 399 trading days)

On the third period representing 250 to 399 trading days of commodity exchange and covering 150 trading days, we observe that all models are better fit without d-Afarma showing the fact that market has short memory and specifically the market only remembers temporal profit up to 4 days and to weaker extent the fifth one too (see table 13, below). The reaction of market is to self correct to ward zero since the AR terms have negative sign. However the AR(1) is stable only in 5% in IGARCH model though it is stable at 1% in all models[3]. Again the expected temporal profit holding all variables constant is zero or the constant has zero coefficient. So the structure of profit does not seem to change in this period compared to the second period.

Information criterions are not able to pick one over the other. Akaike and Shibata pick HYGARCH; Schwarz pick BBR version of FIGARCH and Hannan-Quinn pick IGARCH. This is not conclusive but given the implication that even if selected HYGARCH and BBR are self reject as right model since d-fgarch is insignificant in all of them, though alpha is different from 1 (is greater than one). Moreover d-figarch term in HYGARCH model and constant in both FIGARCH models are unstable[4], showing that these are not appropriate models.

So given the limitation of the data that we have, the best choice is IGARCH but notice that even if we choice HYGARCH, the conclusion is the same as IGARCH. So the above conclusion is only rejected if BBR is right but still since Chung show that the estimation of constant in BBR is problematic given wrong specification of the model (Chung, 1999) and given the constant is less stable in BBR, it is better to accept the above result. However the imposition of ARCH term in the data, given the software G@rch in OxMetrics 5.1 does not allow you to drop it, is causing some fitness problem as observed in negative value in IGARCH and insignificant value in simple GARCH. So it is more logical to say that even though shocks at shorter lag (one day a go) are more important more distance shocks are also important but with very low weight which decline at geometric scale.

[3] See foot note 2 for critical values
[4] See foot note 2 for critical values

Table 13 ARCH/GARCH type of model for last period (250 to 399 trading days) based on normal distribution

HYGARCH			
Variable	Coefficient	Std.Error	Nyblom
AR(1)	-0.59367***	0.1076	0.63684
AR(2)	-0.379602***	0.079949	0.19232
AR(3)	-0.270134***	0.079947	0.14832
AR(4)	-0.452848*	0.076266	0.38133
AR(5)	-0.116565*	0.064989	0.20964
d-Figarch	0.972091	0.40114	0.52047
ARCH(Phi1)	0.435666	0.2413	0.29424
GARCH(Beta1)	1*	0.064416	0.07172
Log Alpha (HY)	0.006932**	0.035413	0.02658
FIGARCH- CHUNG			
Variable	Coefficient	Std.Error	Nyblom
AR(1)	-0.647186***	0.11485	0.59245
AR(2)	-0.444874***	0.097368	0.13491
AR(3)	-0.335458***	0.087597	0.1527
AR(4)	-0.479036***	0.090167	0.33974
AR(5)	-0.1225	0.076928	0.10714
Cst(V)	13.406521***	2.8908	0.51686
d-Figarch	0.10091	0.091269	0.19815
FIGARCH –BBR			
Variable	Coefficient	Std.Error	Nyblom
AR(1)	-0.645895***	0.11244	0.59517
AR(2)	-0.443569***	0.093343	0.13999
AR(3)	-0.334365***	0.084242	0.15279
AR(4)	-0.477778***	0.086818	0.33314
AR(5)	-0.12207	0.074536	0.10915
Cst(V)	6.253625	4.623	0.41479
d-Figarch	0.112019	0.11057	0.30845
GARCH			
Variable	Coefficient	Std.Error	Nyblom
AR(1)	-0.662589***	0.091031	0.48203
AR(2)	-0.478197***	0.081869	0.12116
AR(3)	-0.357188***	0.075334	0.14916
AR(4)	-0.504019***	0.078658	0.39525
AR(5)	-0.11375	0.068829	0.08658
ARCH(Phi1)	0.009819	0.023894	0.05722
GARCH(Beta1)	0.993965***	0.020176	0.0744
IGARCH			
Variable	Coefficient	Std.Error	Nyblom
AR(1)	-0.693797***	0.09807	0.4005
AR(2)	-0.484325***	0.09587	0.10155
AR(3)	-0.362218***	0.08925	0.14152
AR(4)	-0.524638***	0.08109	0.37365
AR(5)	-0.130497*	0.078002	0.07152
ARCH(Phi1)	-0.000005***	0.015883	0.1249
GARCH(Beta1)	1.000005		

Note 3 * significant at 10%, ** significant at 5% and * significant at 1%**

Table 14 Information criterion for different ARCH/GARCH type of model with normal distribution in post shock time

model	HYGARCH	FIGARCH- CHUNG	FIGARCH -BBR	GARCH	IGARCH
Log Likelihood	-405.022	-407.067	-407.037	-407.265	-408.353
Akaike	5.5203	5.520894	5.520498	5.523532	5.524703
Schwarz	5.700938	5.66139	5.660994	5.664028	5.645128
Shibata	5.513628	5.516792	5.516396	5.51943	5.521664
Hannan-Quinn	5.593687	5.577973	5.577577	5.580611	5.573628

But again the limitation of the data is also observed from the effect of distribution assumed in the estimation process. It was observed that information criterions are not able to pick the best among different distributions. The above normal distribution is selected based on stability of parameters since it was not possible to rank them by information. When other distributions are used we found that d-figarch is not significant from zero and constant and some other parameters are not stable (see appendix 3). If we take the result of GARCH and IGARCH all of them except one show that GARCH(Beta1) is equal or statistically equal to one while ARCH(Phi1) is statistically zero. The one exception is skewed student distribution where in GARCH model ARCH(Phi1) is statistically zero and dropping GARCH(Beta1) is found to be economic by information criterion. But constant in variance equation was not stable. So the most logical conclusion is that GARCH(Beta1) is one and ARCH(Phi1) is zero. So the conclusion of the above analysis does hold.

Table 15 Test for ARCH/GARCH effect in post shock

Test	Q test on		Q test on		Residual Based test			F test for ARCH			
TEST	VALUE	PROB.	VALUE	PROB.	TEST	VALUE	PROB.	TEST	DF	VALUE	PROB.
Q(5)			3.939	0.56	RBD(2)	7.854	0.02	ARCH 1-	2,145	1.434	0.24
Q(10)	3.397	0.64	4.334	0.93	RBD(5)	10.87	0.05	ARCH 1-	5,139	0.719	0.61
Q(20)	20.18	0.16	23.764	0.25	RBD(10)	20.90	0.02	ARCH 1-	10,12	0.375	0.96
Q(50)	55.51	0.14	52.368	0.38							

In table 15, above, formal test for ARCH/GARCH effect is done by using the above models but without any memory or cluster of volatility but just constant variance (ARFIMA – model). The above table shows that there is no serial correlation problem, but it seems the serial correlations problems are relatively stronger at longer lags. Q test and F- test show that there is no ARCH or GARCH effect in the model. However Residual Based test show that there is volatility cluster. Now we can check the nature of the data after the HYGARCH version models are fitted to see the change. Note that in all models MA terms are tried but it was observed to create serial correlation problem and is rejected by information criterion. So the models used in this paper are ARFI-M-HYGARCH than ARFIMA-M-HYGARCH.

As we can see it in table 16 below when the models are fitted, all models that introduce d-fgarch as parameter were creating serial correlation problem in the model. Moreover HYGARCH and GARCH models do also show some residual ARCH/GARCH problem. Only IGARCH model is better in solving all ARCH/GARCH problems without increasing the serial correlation in the data. This is good indicator that IGARCH model is more appropriate compared to others.

Table 16 Tests for ARCH/GARCH type of model with normal distribution in post shock time (250 - 399 day of trading)

TEST Type		HYGARCH		FIGARCH-CHUNG		FIGARCH -BBR		GARCH		IGARCH	
	TEST	VALUE	PROB.	VALUE	PROB.	VALUE	PROB.	VALUE	PROB.	VALUE	PROB.
Q test on standardized error	Q(5)										
	Q(10)	2.788	0.733	3.182	0.672	3.182	0.672	3.198	0.669	3.397	0.639
	Q(20)	22.96	0.085	22.373	0.098	22.467	0.096	19.809	0.179	20.183	0.165
	Q(50)	61.564	0.051	60.047	0.066	60.219	0.064	55.847	0.129	55.517	0.135
Q test on squared error	Q(5)	2.942	0.401	1.511	0.912	1.469	0.917	3.889	0.274	3.939	0.268
	Q(10)	3.972	0.86	2.494	0.991	2.476	0.991	4.775	0.781	4.334	0.826
	Q(20)	19.554	0.359	22.469	0.316	22.389	0.32	26.476	0.089	23.762	0.163
	Q(50)	38.493	0.835	45.901	0.638	45.592	0.651	52.928	0.29	52.368	0.308
Residual Based test	RBD(2)	5.57	0.062	0.721	0.697	-23.024	1	1.986	0.371	-0.758	1
	RBD(5)	10.411	0.064	2.394	0.792	-7.916	1	6.158	0.291	2.966	0.705
	RBD(10)	-8.541	1	2.884	0.984	-0.729	1	11.394	0.328	3.888	0.952

So the nature of the temporal profit data generating process does not seem to change but the data generating process of variance did change in this period. The short memory component is lost and the market predicted variability is showing dependence on lagged variability with higher weight given to shorter lags and geometrical decaying weight given to distance lags. Given GARCH(Beta1) is statistically one implies that the market does not have unconditional variance and there is no limit to what level the variance can converge. One possible good side of the intervention is that there is probability that short memory in form hyperbolic memory (d-figarhc = 1) is replacing ARCH(Phi1) effect in some models. Means unconditional variance could possibly exist and the market did become more stable in terms of range of volatility it can take in second period, but it become highly unstable in terms of day to day instability. But the intervention did make the market dynamics in terms temporal profit more predictable, but this could be result of learning by doing than any effect of policy.

Unfortunately in the third period the market again become more unstable as conditional variance again does not exist. Means the long term effect of the heavy handed state policy was to make the unstructured high volatility of temporal profit more structured and very hard to control, while restricting the range of value that conditional variance can take. Means maximum limit on volatility was introduced effectively, though for just short period, but the market become highly unstable with in this limits. Far worst the market become more manipulate-able than less manipulate-able as expected in the introduction of the policy.

<u>The existence of asymmetric volatility in the market</u>

It is widely documented that since positive gain will improve the leverage of sellers but loss will reduce their leverage, and given sellers are more stressed to improve their liquidity than buyers, negative changes are more clustered than positive changes (Nelson, 1991; Engle and Ng, 1993; Rabemananjara, and Zakoian, 1993 and Gloten, etal, 1993). In Ethiopian case since the buyers are rich exporters and the sellers are whole sellers or cooperatives which are facing more liquidity problem compared to exporters, it is logical to expect negative shocks which effect sellers are going to be more clustered than positive shocks which effect exporters. To check this test for asymmetric volatility based on the news impact curve is given in table 17, below. (Engle and Ng, 1993)

Table 17 test for asymmetric volatility based on the news impact curve of Engle and Ng (1993)

Kind of test	1 to 165		166 - 249		250 - 399	
	value	Prob.	value	Prob.	value	Prob.
Sign Bias t-Test	0.29287	0.76962	0.1974	0.84352	1.14771	0.25109
Negative Size Bias t-Test	0.56035	0.57524	0.01158	0.99076	0.29419	0.76861
Positive Size Bias t-Test	1.15444	0.24832	0.56736	0.57047	1.8086	0.07051
Joint Test	1.68818	0.63956	0.88187	0.8298	3.77967	0.28626

In all periods there is no significant sign bias either negative or positive with one exception. In the last period there seems to be positive bias at 10% but not at conventional 5%. This shows in all periods there was symmetric cluster of volatility and the miner exception is the existence of weak positive sign bias. Means in this last period positive changes are more clustered than negative changes. This implies in post volatile months whole sellers have more leverage compared to exporters, which is expected given the heavy handed state policy that is observed in preceding months. So if state policy was meant to improve the leverage of wholesale traders over exporters this could be taken also as indicator of success, but it is not significant enough at 5%.

Reward for risk taking

As can we see it from table 18 below return to risk taking was positive and significant at the first period when the market was having less structured generation of shock to conditional variance. The reward for risk taking was 0.015 or 0.012 percent increase in temporal profit for one unit increase of conditional variance. Moreover once return to risk is taken in to account the constant becomes insignificant showing that the increase in profit in this period was mainly because the market was rewarding risk taking wholesalers not exporters. Moreover in this period ARCH effect become very important having a coefficient equal to 0.44.

However in the second and third period the average return was 0.00012% and 0.0095 %, respectively but it was not significant and there is no change on other parameters. So in the first 165 days of the commodity exchange the washed coffee export market was rewarding risk taking behaviour by wholesalers, but the reward is not significant numerically and statistically since then.

Table 18 reward for risk taking using IGARCH model which is found to be more parsimonious

1 to 165 trading days			
Variable	Coefficient	Std.Error	Nyblom
Cst (M)	-0.55854*	0.28783	0.17637
d-Arfima	-0.42113***	0.053072	0.21725
Cst (V)	12.14292*	6.6967	0.26802
ARCH (Alpha1)	0.441452***	0.093194	0.29074
Asymmetry	-0.32455**	0.1428	0.15452
Tail	2.870228***	0.47024	0.3617
ARCH-in-mean (var)	0.015219***	0.004929	0.1805
GARCH (Beta1)	0.558548		
166 to 249 trading days			
Variable	Coefficient	Std.Error	Nyblom
d-Arfima	-0.52095***	0.14415	0.12292
AR(1)	-0.17362	0.16325	0.09786
AR(2)	-0.20604	0.13814	0.23502
AR(3)	-0.09069	0.13134	0.05413
AR(4)	-0.17278*	0.10059	0.07833
ARCH (Alpha1)	0.258444***	0.044792	0.09361
ARCH-in-mean (var)	0.000156	0.000254	0.26284
GARCH (Beta1)	0.741556		
250 to 399 trading days			
Variable	Coefficient	Std.Error	Nyblom
AR(1)	-0.70264***	0.096554	0.44418
AR(2)	-0.49603***	0.096619	0.0847
AR(3)	-0.37594***	0.087602	0.12564
AR(4)	-0.53759***	0.080566	0.42641
AR(5)	-0.14144*	0.076044	0.06772
ARCH(Alpha1)	0	0.01944	0.12457
ARCH-in-mean (var)	0.009458	0.006983	0.39304
GARCH(Beta1)	1		

Note 4 * significant at 10%, ** significant at 5% and *** significant at 1%

So the effect of the state policy seems to eliminate the risk premium for risk taking wholesalers than to reduce any risk premium that could happen to 'manipulative' and 'rent seeking' exporters. Naturally if exporters were destabilizing the market, there would be negative and significant ARCH-in-mean parameter and should decline over time. But the fact seems to be contradictory to what the assumptions of the state were at that time. This is good indicator that Ethiopia Commodity Exchange should exert some effort in trying to understand the data generating process of prices and temporal profits, before prescribing any policy.

However state claim of speculation is in international market that exporters are hording coffee than exporting it in order to speculate in prices. But the above result cannot test that. However either speculation on export side was there or not, wholesalers where benefiting more before the market second period but not since then.

Conclusion

In this study it is found that the Ethiopian Commodity Exchange (ECX) temporal profit on sell of washed coffee for export have three different data generating process. In terms of profit in the initial period reward for whole sellers is observed to increase with increase in volatility. But the market is this period showing week form of volatility cluster, if there is any. Though there is some evidence that the volatility in their period was not structural, given the limitation of the data size, the information criterion pick IGARCH model which showed there is short term volatility cluster at one auto regressive lag, which is dominated by geometrically decaying volatility cluster. Moreover the market has short memory of shocks to temporal profit. As result the market was less manipulate-able. It is possible price were more volatile in this time because whole sellers were rewarded by increased volatility but the reward was for whole sellers not exporters, as claimed by the state.

In second stage the market become more predictable. The best prediction would be to say the market will correct temporal profit moments of the last 4 to 5 days. But this was not significant enough, as these parameters were not significant, to have impact on the market. The problem is serial correlation was not eliminated without these parameters. In this time volatility become more structural with geometric decaying memory. However even though there was short term (one lag) volatility cluster its representation by either short memory or one lag memory was not clear but information criterions pick the one day. It is possible the memory is close to one full day but not just one. The basic point is that variance of temporal profit did increase but since unconditional variance have high chance to exist in this period the maximum limit of variability was reduced while the day to day variability is increased. Moreover whole sellers lost their reward related to increased variability.

If we assume this period is related to lagged effect of government heavy handed intervention, or assuming exporters store coffee to satisfy their short position on international market, it seems state intervention in these period was misguided and did clearly has unintended consequences which are opposite to justification given to the intervention. In both this period and the initial period, volatility was symmetric and neither whole sellers nor exporters had any leverage advantage.

In the third period the predictability of the market becomes significant and a market was observed to correct the direction of its temporal profit trend up to 4 to 5 lags. In this period the short term volatility cluster is lost and the volatility cluster becomes limitless but with more geometrically declining weight which increase with lag. Means lower lags have more effect on current volatility but even distant variability also has effect though to much lower scale. Means the market become more complex to stabilize, without long lasting intervention. Reward was not related to level of volatility but it was observed the leverage of whole sellers was observed to increase in comparison to exporters, though to weaker extent. This is the only visible improvement, if the objective of the intervention was to balance the power of whole sellers and exporters.

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Appendix 1

All distributions pre volatile months

1. ### Appindex. 1. 1 Hygarch model just the ARCH/GARCH type model only

Normal			
Variable	Coefficient	Std.Error	Nyblom
Cst (Var)	34.022485***	6.6181	0.35571
d-Figarch	0	.NaN	0.5395
ARCH(Phi1)	0	0.083609	0.66549
GARCH(Beta1)	0.907612	49.005	.NaN
Log Alpha (HY)	34.022485***	6.6181	0.35571
Student			
Variable	Coefficient	Std.Error	Nyblom
Cst (Var)	.NaN	.NaN	.NaN
d-Figarch	0.00058***	0.000104	0.38601
ARCH(Phi1)	0	0.55145	0.09125
GARCH(Beta1)	3.448091**	1.48	0.4508
Log Alpha (HY)	5.67614***	0.84134	0.38574
Skewed student			
Variable	Coefficient	Std.Error	Nyblom
Cst (Var)	.NaN	.NaN	.NaN
d-Figarch	0.206631	0.2598	0.4464
ARCH(Phi1)	0	0.37571	0.10902
GARCH(Beta1)	.NaN	.NaN	.NaN
Asymmetry	-0.364707**	0.15431	0.15858
Tail	3.055444***	1.138	0.52864
Log Alpha (HY)	0.805421	0.81703	0.49749
GED			
Variable	Coefficient	Std.Error	Nyblom
Cst (Var)	.NaN	.NaN	.NaN
d-Figarch	0.00084	8.26E-05	0.24404
ARCH(Phi1)	0.027816	0.59561	0.15187
GARCH(Beta1)	0.167792	0.57821	0.15444
G.E.D.(DF)	1.109559***	0.22843	0.28776
Log Alpha (HY)	5.142405***	0.19988	0.24389

Note - NaN means it is dropped by information criterion. For other tables they are ignored

Appindex 1. 2 Hygarch model information criterion

Distribution	Normal	Student	Skewed student	GED
Log Likelihood	-521.922	-512.173	-506.287	-513.603
Akaike	6.438068	6.319188	6.271795	6.348812
Schwarz	6.551478	6.432597	6.423008	6.481123
Shibata	6.435515	6.316634	6.267325	6.345363
Hannan-Quinn	6.484108	6.365228	6.333182	6.402525

Appindex 1. 3 FIGARCH - Chung model just the ARCH/GARCH type model only

Normal			
Variable	Coefficient	Std.Error	Nyblom
Cst(V)	34.022552***	5.429	0.35574
d-Figarch	-0.000005	0.058681	0.08026
Student			
Variable	Coefficient	Std.Error	Nyblom
Cst(V)	37.292792	10.733***	0.45576
d-Figarch	0.072134	0.09278	0.08229
Student(DF)	3.830632	1.0505***	0.51779
Skewed student			
Variable	Coefficient	Std.Error	Nyblom
Cst(V)	41.844784***	15.548	0.38457
d-Figarch	0.177878*	0.10032	0.12561
Asymmetry	-0.26779**	0.13227	0.20387
Tail	4.071776***	0.96835	0.49331
GED			
Variable	Coefficient	Std.Error	Nyblom
Cst(V)	0.799075	134.97	.NaN
d-Figarch	1***	0	0.29232
GARCH(Beta1)	1***	0.014836	0.09755
G.E.D.(DF)	1.117187***	0.13278	0.31835

Appindex 1. 4 FIGARCH - Chung model information criterion

Distribution	Normal	Student	Skewed student	GED
Log Likelihood	-521.922	-511.96	-508.956	-513.232
Akaike	6.413678	6.30436	6.279945	6.332094
Schwarz	6.489284	6.39887	6.393355	6.445504
Shibata	6.412525	6.30257	6.277392	6.329541
Hannan-Quinn	6.444371	6.34273	6.325985	6.378134

Appindex 1. 5. FIGARCH – BBM - model information criterion

Distribution	Normal	Student	Skewed student	GED
Log Likelihood	-521.922	-511.857	-508.956	-513.056
Akaike	6.413678	6.303137	6.279945	6.329955
Schwarz	6.489284	6.397645	6.393355	6.443365
Shibata	6.412525	6.30135	6.277392	6.327402
Hannan-Quinn	6.444371	6.341504	6.325985	6.375995

Appindex 1. 5 FIGARCH – BBM - model just the ARCH/GARCH type model only

Normal			
Variable	Coefficient	Std.Error	Nyblom
Cst(V)	34.022515**	16.718	0.35559
d-Figarch	-0.000005	0.057449	0.53932
Student			
Variable	Coefficient	Std.Error	Nyblom
Cst(V)	21.836711	16.567	0.43112
d-Figarch	0.093998	0.12546	0.53677
Student(DF)	3.591383***	0.97033	0.51393
Skewed student			
Variable	Coefficient	Std.Error	Nyblom
Cst(V)	41.844784***	15.548	0.38457
d-Figarch	0.177878*	0.10032	0.12561
Asymmetry	-0.26779**	0.13227	0.20387
Tail	4.071776***	0.96835	0.49331
GED			
Variable	Coefficient	Std.Error	Nyblom
Cst(V)	21.77802	20.231	0.35978
d-Figarch	0.062175	0.12325	0.4309
GARCH(Beta1)	0.059488	0.12182	0.12757
G.E.D.(DF)	1.120091***	0.17584	0.29765

Appindex 1. 6 GARCH – model just the ARCH/GARCH type model only

Normal			
Variable	Coefficient	Std.Error	Nyblom
ARCH(Alpha1)	0.001497***	0.068618	0.27398
GARCH(Beta1)	0.999995***	0.057696	0.20291
Student			
Variable	Coefficient	Std.Error	Nyblom
Cst(V)	37.622455	9.3329***	0.61042
Student(DF)	3.64389	0.98322***	0.56792
Skewed student			
Variable	Coefficient	Std.Error	Nyblom
Cst(V)	37.045004***	8.6935	0.66403
Asymmetry	-0.171447	0.10624	0.17099
Tail	3.804166***	1.0152	0.57793
GED			
Variable	Coefficient	Std.Error	Nyblom
ARCH(Alpha1)	0.001834	0.16064	0.37469
GARCH(Beta1)	1***	0.13452	0.33916
G.E.D.(DF)	1.080763***	0.27328	0.34059

Appindex 1. 7 GARCH - model information criterion

Distribution	Normal	Student	Skewed student	GED
Log Likelihood	-521.277	-512.386	-510.956	-512.777
Akaike	6.405816	6.297392	6.292151	6.314356
Schwarz	6.481423	6.372998	6.386659	6.408864
Shibata	6.404664	6.29624	6.290365	6.31257
Hannan-Quinn	6.436509	6.328085	6.330518	6.352723

Appindex 1. 8 IGARCH – model just the ARCH/GARCH type model only

Normal			
Variable	Coefficient	Std.Error	Nyblom
ARCH(Alpha1)	-0.000005	0.032427	0.04121
GARCH(Beta1)	1.000005		
Student			
Variable	Coefficient	Std.Error	Nyblom
ARCH(Alpha1)	0	0.0048	0.17275
Student(DF)	3.990074***	0.86492	0.53578
GARCH(Beta1)	1		
Skewed student			
Variable	Coefficient	Std.Error	Nyblom
Cst(V)	9.424733*	4.9968	0.35102
ARCH(Alpha1)	0.393433***	0.11523	0.34563
Asymmetry	-0.338974***	0.12006	0.21284
Tail	3.067447***	0.55621	0.42737
GARCH(Beta1)	0.606567		
GED			
Variable	Coefficient	Std.Error	Nyblom
ARCH(Alpha1)	0	0.014836	0.09756
G.E.D.(DF)	1.117248***	0.13279	0.3183
GARCH(Beta1)	1		

Appindex 1. 9 IGARCH - model information criterion

Distribution	Normal	Student	Skewed student	GED
Log Likelihood	-521.922	-512.452	-506.788	-513.232
Akaike	6.401483	6.298195	6.253506	6.307704
Schwarz	6.458188	6.373801	6.366916	6.38331
Shibata	6.400829	6.297042	6.250953	6.306551
Hannan-Quinn	6.424503	6.328888	6.299546	6.338397

Appendix 2

All distributions volatile months

1. Appindex. 2. 10 Hygarch model just the ARCH/GARCH type model only

Normal			
Variable	Coefficient	Std.Error	Nyblom
d-Figarch	1***	0.10936	0.11195
ARCH(Phi1)	0	0.24182	0.1733
GARCH(Beta1)	0.76394***	0.12562	0.17593
Log Alpha (HY)	0.003088	0.039565	0.57458
Student			
Variable	Coefficient	Std.Error	Nyblom
Cst(V)	0	2.2509	0.02534
d-Figarch	1***	0.1596	0.0433
ARCH(Phi1)	0.132657	0.26221	0.07996
GARCH(Beta1)	0.775937***	0.025436	0.10844
Student(DF)	100***	19.445	3.76011
Log Alpha (HY)	-0.016407	0.034587	0.4494
Skewed student			
Variable	Coefficient	Std.Error	Nyblom
d-Figarch	1***	0.12668	0.03245
ARCH(Phi1)	0.170304	0.2528	0.09947
GARCH(Beta1)	0.776255***	0.16535	0.07029
Asymmetry	0.082759	0.55421	0.1124
Tail	100***	14.709	2.82638
Log Alpha (HY)	-0.001938	0.042765	0.48926
GED			
Variable	Coefficient	Std.Error	Nyblom
d-Figarch	0.823992***	0.021734	0.95231
ARCH(Phi1)	0.593599***	0.018893	0.95231
GARCH(Beta1)	0.595529***	0.00038097	1.9456
G.E.D.(DF)	0.897723	2.4553	0.49423
Log	0.645665***	0.0012338	0.95226

Appindex 2. 11 Hygarch model information criterion

Distribution	Normal	Student	Skewed student	GED
Log Likelihood	-308.006	-310.071	-305.716	-288.225
Akaike	7.547754	7.62074	7.540863	7.124396
Schwarz	7.808199	7.910123	7.859184	7.442717
Shibata	7.527624	7.596219	7.51158	7.095113
Hannan-Quinn	7.652451	7.737069	7.668825	7.252358

Appindex 2. 12 FIGARCH - Chung model just the ARCH/GARCH type model only

Normal			
Variable	Coefficient	Std.Error	Nyblom
d-Figarch	1***	0.051456	0.03381
GARCH(Beta1)	0.73663***	0.069225	0.09483
Student			
Variable	Coefficient	Std.Error	Nyblom
d-Figarch	1***	0.052632	0.034
GARCH(Beta1)	0.736751***	0.070793	0.09224
Student(DF)	99.999995***	11.585	2.7866
Skewed student			
Variable	Coefficient	Std.Error	Nyblom
d-Figarch	1***	0.14584	0.03451
GARCH(Beta1)	0.73994***	0.21175	0.09456
Asymmetry	0.080437	0.77982	0.07994
Tail	99.999995***	12.76	2.73993
GED			
Variable	Coefficient	Std.Error	Nyblom
d-Figarch	1***	0.10538	0.12795
GARCH(Beta1)	0.76601***	0.090066	0.21022
G.E.D.(DF)	2.52122***	1.1614	0.09316

Appindex 2. 13 FIGARCH - Chung model information criterion

Distribution	Normal	Student	Skewed student	GED
Log Likelihood	-305.877	-305.996	-305.942	-307.8
Akaike	7.449456	7.476106	7.498625	7.519041
Schwarz	7.652024	7.707613	7.75907	7.750548
Shibata	7.43694	7.459983	7.478496	7.502919
Hannan-Quinn	7.530887	7.56917	7.603322	7.612105

Appindex 2. 5. FIGARCH – BBM - model information criterion

Distribution	Normal	Student	Skewed student	GED
Log Likelihood	-305.851	-305.971	-305.942	-307.8
Akaike	7.448826	7.475497	7.498625	7.519041
Schwarz	7.651394	7.707003	7.75907	7.750548
Shibata	7.43631	7.459374	7.478496	7.502919
Hannan-Quinn	7.530257	7.56856	7.603322	7.612105

Appindex 2. 14 FIGARCH – BBM - model just the ARCH/GARCH type model only

Normal			
Variable	Coefficient	Std.Error	Nyblom
d-Figarch	0.987105***	0.050335	0.03585
GARCH(Beta1)	0.718097***	0.07471	0.12991
Student			
Variable	Coefficient	Std.Error	Nyblom
d-Figarch	0.987154***	0.051216	0.03556
GARCH(Beta1)	0.718326***	0.075887	0.12603
Student(DF)	99.999995***	10.92	2.73575
Skewed student			
Variable	Coefficient	Std.Error	Nyblom
d-Figarch	1***	0.16347	0.0315
GARCH(Beta1)	0.739911***	0.27122	0.09458
Asymmetry	0.080378	0.91445	0.07995
Tail	99.999995***	13.748	2.74003
GED			
Variable	Coefficient	Std.Error	Nyblom
d-Figarch	1***	0.095785	0.12849
GARCH(Beta1)	0.765999***	0.085118	0.21024
G.E.D.(DF)	2.521208**	1.0157	0.09314

Appindex 2. 15 GARCH – model just the ARCH/GARCH type model only

Normal			
Variable	Coefficient	Std.Error	Nyblom
ARCH(Alpha1)	0.254318***	0.063159	0.43973
GARCH(Beta1)	0.740031***	0.04666	0.28119
Student			
Variable	Coefficient	Std.Error	Nyblom
ARCH(Alpha1)	0.258388***	0.064644	0.44734
GARCH(Beta1)	0.738563***	0.047386	0.28564
Student(DF)	99.999995***	8.8991	2.87165
Skewed student			
Variable	Coefficient	Std.Error	Nyblom
ARCH(Alpha1)	0.25855***	0.059667	0.4799
GARCH(Beta1)	0.740433***	0.047578	0.30782
Asymmetry	0.079291	0.41798	0.07905
Tail	99.999995***	8.5542	2.76966
GED			
Variable	Coefficient	Std.Error	Nyblom
ARCH(Alpha1)	0.235699***	0.066905	0.53582
GARCH(Beta1)	0.765317***	0.040923	0.48854
G.E.D.(DF)	2.522617**	1.0427	0.0938

Appindex 2. 16 GARCH - model information criterion

Distribution	Normal	Student	Skewed student	GED
Log Likelihood	-305.87	-305.995	-305.942	-307.799
Akaike	7.449295	7.476061	7.49862	7.519034
Schwarz	7.651863	7.707567	7.759065	7.75054
Shibata	7.436779	7.459938	7.478491	7.502911
Hannan-Quinn	7.530725	7.569124	7.603317	7.612098

Appindex 2. 17 IGARCH – model just the ARCH/GARCH type model only

Normal			
Variable	Coefficient	Std.Error	Nyblom
ARCH(Alpha1)	0.263335***	0.045665	0.09474
GARCH(Beta1)	0.736665		
Student			
Variable	Coefficient	Std.Error	Nyblom
ARCH(Alpha1)	0.26325***	0.046279	0.09226
Student(DF)	99.999995***	11.696	2.78657
GARCH(Beta1)	0.73675		
Skewed student			
Variable	Coefficient	Std.Error	Nyblom
ARCH(Alpha1)	0.260057***	0.051479	0.09455
Asymmetry	0.080433	0.40627	0.07995
Tail	99.999995***	11.765	2.73991
GARCH(Beta1)	0.739943		
GED			
Variable	Coefficient	Std.Error	Nyblom
ARCH(Alpha1)	0.233988***	0.037357	0.21019
G.E.D.(DF)	2.521225**	1.0151	0.09314
GARCH(Beta1)	0.766012		

Appindex 2. 18 IGARCH - model information criterion

Distribution	Normal	Student	Skewed student	GED
Log Likelihood	-305.877	-305.996	-305.942	-307.8
Akaike	7.425647	7.452297	7.474816	7.495232
Schwarz	7.599277	7.654865	7.706322	7.6978
Shibata	7.416321	7.439781	7.458693	7.482716
Hannan-Quinn	7.495444	7.533727	7.567879	7.576663

Appendix 3
All distributions post volatile months

1. Appindex. 3. 19 Hygarch model just the ARCH/GARCH type model only

Normal			
Variable	**Coefficient**	**Std.Error**	**Nyblom**
d-Figarch	0.972091	0.40114	0.52047
ARCH(Phi1)	0.435666	0.2413	0.29424
GARCH(Beta1)	1*	0.064416	0.07172
Log Alpha (HY)	0.006932**	0.035413	0.02658
Student			
Variable	**Coefficient**	**Std.Error**	**Nyblom**
d-Figarch	0.818817**	0.41291	0.28632
ARCH(Phi1)	0.568898**	0.26	0.19488
GARCH(Beta1)	1***	0.078701	0.04653
Student(DF)	4.005697*	2.2142	0.18875
Log Alpha (HY)	0.015616	0.085334	0.04344
Skewed student			
Variable	**Coefficient**	**Std.Error**	**Nyblom**
d-Figarch	0.804531	0.57429	0.27101
ARCH(Phi1)	0.581251**	0.25124	0.17946
GARCH(Beta1)	1***	0.14854	0.05496
Asymmetry	-0.169265	0.1581	0.02984
Tail	3.759892	2.6717	0.1295
Log Alpha (HY)	0.021036	0.18473	0.04981
GED			
Variable	**Coefficient**	**Std.Error**	**Nyblom**
Cst(V)	11.10213***	2.2015	0.55348
d-Figarch	0	.NaN	0.60073
ARCH(Phi1)	0.208475	0.15006	0.139
G.E.D.(DF)	1.285243***	0.25531	0.14508
Log Alpha (HY)	0.676873	2.1046	.NaN

Appindex 3. 20 Hygarch model information criterion

Distribution	Normal	Student	Skewed student	GED
Log Likelihood	-405.022	-402.086	-401.089	-403.198
Akaike	5.5203	5.494474	5.494518	5.509309
Schwarz	5.700938	5.695183	5.715298	5.710018
Shibata	5.513628	5.486304	5.484711	5.501139
Hannan-Quinn	5.593687	5.576015	5.584214	5.590851

Appindex 3. 21 FIGARCH - Chung model just the ARCH/GARCH type model only

Normal			
Variable	Coefficient	Std.Error	Nyblom
Cst(V)	13.406521***	2.8908	0.51686
d-Figarch	0.10091	0.091269	0.19815
Student			
Variable	Coefficient	Std.Error	Nyblom
d-Figarch	0.419868***	0.037947	0.89187
Student(DF)	3.672182***	0.48844	0.29264
Skewed student			
Variable	Coefficient	Std.Error	Nyblom
Cst(V)	13.802984***	3.5076	0.67673
d-Figarch	0.126923	0.098508	0.1496
Asymmetry	-0.090088	0.11401	0.06612
Tail	7.164089**	3.4417	0.29361
GED			
Variable	Coefficient	Std.Error	Nyblom
Cst(V)	13.432977***	3.0598	0.51908
d-Figarch	0.109527	0.10719	0.13111
G.E.D.(DF)	1.303598***	0.25921	0.09922

Appindex 3. 22 FIGARCH - Chung model information criterion

Distribution	Normal	Student	Skewed student	GED
Log Likelihood	-407.067	-406.148	-404.135	-403.937
Akaike	5.520894	5.508642	5.508471	5.492498
Schwarz	5.66139	5.649138	5.689109	5.653065
Shibata	5.516792	5.50454	5.501799	5.487184
Hannan-Quinn	5.577973	5.565721	5.581858	5.557731

Appindex 3. 5. FIGARCH – BBM - model information criterion

Distribution	Normal	Student	Skewed student	GED
Log Likelihood	-407.037	: -398.600	-403.978	-403.9
Akaike	5.520498	5.447998	5.506372	5.491997
Schwarz	5.660994	5.648707	5.68701	5.652564
Shibata	5.516396	5.439828	5.499701	5.486683
Hannan-Quinn	5.577577	5.52954	5.57976	5.55723

Appindex 3. 23 FIGARCH – BBM - model just the ARCH/GARCH type model only

Normal			
Variable	Coefficient	Std.Error	Nyblom
Cst(V)	6.253625	4.623	0.41479
d-Figarch	0.112019	0.11057	0.30845
Student			
Variable	Coefficient	Std.Error	Nyblom
d-Figarch	0.777604***	4.25E-51	0.26388
ARCH(Phi1)	0.300941***	6.35E-05	0.26109
GARCH(Beta1)	0.969285***	4.37E-52	0.11231
Student(DF)	8.080077	4.8992	0.41358
Skewed student			
Variable	Coefficient	Std.Error	Nyblom
Cst(V)	5.35632	3.8359	0.50491
d-Figarch	0.164168	0.15767	0.41169
Asymmetry	-0.10379	0.12513	0.05216
Tail	6.198903**	2.9988	0.31784
GED			
Variable	Coefficient	Std.Error	Nyblom
Cst(V)	5.840141	4.8971	0.39496
d-Figarch	0.12671	0.14068	0.32984
G.E.D.(DF)	1.283441***	0.25653	0.10954

Appindex 3. 24 GARCH – model just the ARCH/GARCH type model only

Normal			
Variable	Coefficient	Std.Error	Nyblom
ARCH(Alpha1)	0.009819	0.023894	0.05722
GARCH(Beta1)	0.993965***	0.020176	0.0744
Student			
Variable	Coefficient	Std.Error	Nyblom
ARCH(Alpha1)	0.008318	0.13497	0.06642
GARCH(Beta1)	1***	0.10555	0.05518
Student(DF)	3.487647	5.4805	0.23378
Skewed student			
Variable	Coefficient	Std.Error	Nyblom
Cst(V)	11.430962***	2.405	0.7124
ARCH(Alpha1)	0.228285	0.14871	0.22882
Asymmetry	-0.09984	0.12485	0.05656
Tail	6.227378**	2.9057	0.45016
GED			
Variable	Coefficient	Std.Error	Nyblom
ARCH(Alpha1)	0.003691	0.030255	0.0882
GARCH(Beta1)	0.99938***	0.02382	0.09555
G.E.D.(DF)	1.177349***	0.34725	0.15531

Appindex 3. 25 GARCH - model information criterion

Distribution	Normal	Student	Skewed student	GED
Log Likelihood	-407.265	-405.241	-403.28	-404.024
Akaike	5.523532	5.496549	5.497063	5.493653
Schwarz	5.664028	5.637045	5.677702	5.65422
Shibata	5.51943	5.492447	5.490392	5.488339
Hannan-Quinn	5.580611	5.553628	5.570451	5.558886

Appindex 3. 26 IGARCH – model just the ARCH/GARCH type model only

Normal			
Variable	Coefficient	Std.Error	Nyblom
ARCH(Alpha1)	-0.000005***	0.015883	0.1249
GARCH(Beta1)	1.000005		
Student			
Variable	Coefficient	Std.Error	Nyblom
ARCH(Alpha1)	0	0.005877	0.15918
Student(DF)	6.085035**	2.9608	0.53297
GARCH(Beta1)	1		
Skewed student			
Variable	Coefficient	Std.Error	Nyblom
ARCH(Alpha1)	0	0.004937	0.18709
Asymmetry	-0.087576	0.096545	0.08134
Tail	6.135338**	2.9318	0.52325
GARCH(Beta1)	1		
GED			
Variable	Coefficient	Std.Error	Nyblom
Cst(V)	0.040449	0.097314	0.1156
ARCH(Alpha1)	0.002591	0.033465	0.1425
G.E.D.(DF)	1.176555***	0.33558	0.16013
GARCH(Beta1)	0.997409		

Appindex 3. 27 IGARCH - model information criterion

Distribution	Normal	Student	Skewed student	GED
Log Likelihood	-408.353	-405.753	-405.373	-404.074
Akaike	5.524703	5.503375	5.511644	5.49432
Schwarz	5.645128	5.643872	5.672211	5.654887
Shibata	5.521664	5.499273	5.50633	5.489006
Hannan-Quinn	5.573628	5.560455	5.576877	5.559553