

Islamic vs Conventional Canadian stock markets : what difference ?

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13 April 2020

Online at https://mpra.ub.uni-muenchen.de/99608/ MPRA Paper No. 99608, posted 11 May 2020 11:48 UTC

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Abstract

This study empirically assesses the relationship between inflation and stock return in conventional and Islamic Canadian stock markets. The study has covered monthly data for the period 2004:M08-2018 :M4 of canadian economy. We propose a multivariate X-MGARCH or Xassess the dependence MGARCH-X volatility model to of Conventional and Islamic canadian stock market returns on inflation (expected and/or unexpected inflation) and volatility dynamic interdependence of returns (first and second moments). We also examine the constant and dynamic of conditional correlation in both stock market. The main result supports the hypotheses of constant conditional correlation (CCC) and Fisher hypothesis for Islamic canadian stock market. While *the Conventional* stock market is an efficient one. The volatility spillover is examined estimating an X-**DVECH** model. The dynamic conditional correlation (**DCC**) provides evidence of cross border relationship within stocks. We do find also evidence of negative (positive) significant effect of inflation on Islamic (conventional) stock market return volatility.

Keywords: Conventional /Islamic Canadian stock return, Conditional Correlations (CC), Dynamic CC (DCC) and Constant CC models (CCC), Fisher hypothesis, MGARCH -DVECH model, X-MGARCH and X-MGARCH-X models.

JEL classification: C22, G01, G11, G14.

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I. Introduction

Stock market plays a vital role in any country's economic growth. A healthy stock market is considered relevant for economic growth by channelizing capital toward investors and entrepreneurs.

The first two moments respectively called mean and variance of return series have been investigated extensively in the univariate finance literature to understand the trading dynamics of risk and returns in the financial asset markets. As references, reader can see for example (Bollerslev, Engle, & Wooldridge, 1988) and (Bera, 1980), among others.¹

For modeling the first moment, the correlation between stock price and inflation has been explored intensively in literature. (Fisher, 1930) states that the *expected real rate of return* **is independent** of *expected inflation*. Fisher hypothesis, therefore, predicts a **positive** homogenous relationship between *stock returns and inflation*.² In accordance with Fisher, (Fama & Schwert, 1977) argued that the *expected nominal return* of an asset is the sum of the *expected real return* of the asset and the *expected inflation* rate, see (Wohlwend & Goller, 2011). For an empiral review reader can see (Neifar & Harzallah, 2020) Table 12.

For the second moment, there are three main ways of modelling financial volatility (namely : implied volatility, realized volatility, and conditional volatility or conditional correlation), see (Aftab, Beg, Sun, & Zhou, 2019). In this paper we use both the conditional volatility and conditional correlation approaches to provide predictions of volatility and correlations of returns.

¹ These articles use various modeling issues e.g. functional form and dependence.

² In other words, Fisher hypothesis implies that *stocks offer a hedge against inflation*.

Volatility modelling in this paper has been emerged from modeling means and volatilities of returns within the multivariate framework. Within this framework, the shocks to volatility from one market is allowed to affect both the risk and return of the other markets. The dynamic dependence of multivariate financial assets provides rich sources of volatility transmission that helps the investors to play active role in financial transactions. In addition the multivariate extension to univariate GARCH allows volatility spillovers effects across markets jointly. Directional causality between assets returns can be established among the securities by statistical testing. The multivariate extension to univariate model was first introduced by (Engle & Granger, 1987) in the ARCH context, and (Bollerslev, Engle, & Wooldridge, 1988) in the GARCH context. This multivariate GARCH is known as VECH model because of its structure. The general MGARCH model is so flexible that not all the parameters can be estimated. For this reason, we consider three MGARCH models that reparameterize the model to be more parsimonious: the diagonal vech model (DVECH), the constant conditional correlation model (CCC) and the dynamic conditional correlation model (DCC). For general introductions to MGARCH model see (Bollerslev, Engle, & Wooldridge, 1988), (Bollerslev, Engle, 1994), (Bauwens, Laurent, & Rombouts, & Nelson, 2004), (Silvennoinen & Terasvirta, 2009), and (Engle R. F., 2009).

For joint estimation of the multivariate mean-variance models, we use Student t- distribution as one might not want to perform a maximum likelihood estimation using normal distribution (because the normality assumption of unconditional volatility of innovation do not hold, see (Enders, 2014)). The asymptotic chi-square test for volatility spillovers effect is constructed.

The aim of this paper is to compare the Conventional and Islamic canadian stock returns dynamic. Monthly data covering period from 2004M08 to 2018M04 are then taken for analysis. The first objectif is

to test inflation hedging abilities of stock price using Fisher hypothesis and (Fama & Schwert, 1977)'s approach in bivariate framework. The second objectif is the application of the MGARCH model to Canadian Islamic and Conventional stock market to reveals if these financial markets are interdependent and to see if each volatility is predictable.

This paper is organized as follow. Section II describes the sources, statistical properties, and preliminary results of the data. In section III, model methodology is discussed for bivariate framework. Specification of mean (subsection A) is followed by different considered patterns for volatility (subsection B). Real application of the proposed model is reported in section IV. Two canadian stock market are compared ; Conventional and Islamic market. Finally, section V concludes the paper.

II. Data Properties and Preliminary Results

In this paper, the study use log-changes in both Stock prices; Conventional Canadian Stick Index (CCSI) and DJ Islamic Canadian Price Index (DJICPI)) and in the consumer price index (CPI) as a proxy for inflation. Monthly data covering period from 2004M08 to 2018M04 of Stock prices (CCSI and DJICPI), consumer price index (CPI), and industrial production index (IIP) will be taken for analysis. All data are collected form OCDE (Organisation de Cooperation et de Developpement Economique). We denote by

$$RC_{t} = \log(\text{CCSI}_{t}) - \log(\text{CCSI}_{t-1}) \quad (1)$$

$$RI_{t} = \log(\text{DJICPI}_{t}) - \log(\text{DJICPI}_{t-1}) \quad (2)$$

and

$$I_t = \log(\text{CPI}_t) - \log(\text{CPI}_{t-1}) = \Delta \text{LCPI}_t \quad (3)$$

t = 1, ..., T = 165, the Conventional and Islamic stock returns and Inflation. Real activity in the economy will be measured by Index of

Industrial Production in log (LIIP). In addition, the difference between RI_t and I_t ($RI_t - I_t$) represents the real stock return at *t* th period for Islamic marcket and difference between RC_t and I_t ($RC_t - I_t$) represents the conventional real stock return at *t* th period.

We start with an inspection of the Monthly returns RC_t and RI_t . To illustrate, Figure 1 plots the monthly stock returns of RI and RC from 2004M08 to 2018M04. The results in Figure 1 show that the movement of stock returns is both positive and negative. It can be noted that the returns fluctuate around the mean value. Larger fluctuations tend to cluster together followed by periods of calmness.³ This is the general norm with stock returns. Volatility clustering was higher in the period of 2008-2009 when there was a global financial crisis.



Figure 1: Stock returns RI and RC evolution from 2004M08 to 2018M04.

Table 1 (and Figure 5) show the descriptive statistics for the stock returns RI and RC. The data from Canada shows that skewness statistics are negative, indicating that the returns are not symmetric and the distribution has a long left tail. In addition, the kurtosis is way over 3 suggesting that the underlying time series data is heavily tailed and sharply peaked when compared to a normal distribution. In Table 1 the descriptive statistics show that the Conventional market observed mean

³ (Fama, 1981) noted that stock returns tend to fluctuate thereby exhibiting volatility clustering, where large returns are usually followed by small returns.

monthly return of 0.3996 %, way almost similar to the Islamic market which had 0.2923%. The volatility measured by the standard deviation shows that the Conventional market had a deviation of 3.7060 % and the Islamic market had 7.4736% which was higher in volatility than Conventional market. This implies that both markets are different in volatility. The more the market is volatil, the higher the chances of getting high rates of returns but with more risk.

The Jarque - Bera statistics rejects the normality assumption. Hence, confirming the general norm that stock returns are not normally distributed and skewed.

We conduct ADF, PP (and KPSS) tests in order to test for Unit root (and stationarity). The results from theee tests show that the time series data are stationary. The ADF and PP tests statistics reject the null hyphotheis that there is an existence of a unit root in the returns data series. In this case, these test rejects the null hypothesis of a unit root in time series in all three levels of significance (see Annexe Table 4).

LM-Statistic are statistically significant, suggesting the presence of ARCH in the stock returns. Both the RI and RC produced similar results. The test was carried using the lag order of q = 1, ..., 5.

Table 3 presents the results of these tests.



Figure 2 : RI and RC in squared value.

By MA filter,⁴ we decompose the inflation into its trend (expected inflation; EI_t) and unexpected deviations from the trend : unexpected inflation; UEI_t :

$$UEI_t = I_t - EI_t \quad (4)$$

Figure 1 illustrate 3 type of inflation ; actual inflation (I_t) , expected inflation, and unexpected inflation. $EI_t UEI_t$



Figure 3: Inflation (I_t) , Expected Inflation (EI_t) , and Unexpected Inflation (UEI_t) pattern.

III. Methodology

Consider a bivariate return series $R_t = (R_{1t}, R_{2t})' = (RC_t, RI_t)'$ be a vector of Conventional and Islamic returns of 2 Canadian assets at time t (t = 2, 3, ..., T = 165). The set of information available at time t is denoted by Ψ_{t-1} . We adopt the same approach as the univariate case by rewriting the series as

$$Y_t = \mu_t + \varepsilon_t \ (5)$$

where $Y_t = R_t$ (nominal return) or $R_t - I_t \cdot \iota$ (real return), I_t is the rate of inflation at time t and $\iota = (1, 1)$. $\mu_t = E[Y_t/\Psi_{t-1}]$ is the conditional expectation of Y_t given the past information Ψ_{t-1} , and $\varepsilon_t =$

⁴ This is done by STATA version 15. More details are given in (Neifar & Harzallah, 2020).

 $[\varepsilon_{1t}, \varepsilon_{2t}]$ is the shock or innovation of the series at time t. The ε_t process is assumed to follow the conditional expectation of a multivariate time series model

$$\varepsilon_t / \Psi_{t-1} = H_t^{0.5} \nu_t, (6)$$
$$H_t = \operatorname{Cov}(\varepsilon_t | \Psi_{t-1}),$$

where $v_t = [v_{1t}, v_{2t}]$ is the independent and identically distributed (i.i.d.) random vectors of order 2 ×1 with $E[v_t] = 0$ and $E[v_t v_t'] = I_2$, where I_2 is the identity matrix. The conditional covariance matrix H_t of ε_t given Ψ_{t-1} is assumed to be 2 × 2 positive-definite matrix.

 μ_t and H_t can have different specifications. Here after, we propose some ones.

A. Specifications of μ_t

In this section we discuss how do research regarding the inflation hedging abilities. The inflation hedging abilities of stock price can be tested using Fisher hypothesis and the approach of (Fama & Schwert, 1977). In the next subsections, we explain respectively how to validate each of these hypothesis : Fisher hypothesis and the approach of (Fama & Schwert, 1977).

1. Fisher Hypothesis

(Fisher, 1930) hypothesis implies that *stocks offer a hedge against inflation*. In other words, Fisher hypothesis states that the *expected real rate of return* **is independent** of *expected inflation*. Fisher hypothesis, therefore, predicts a **positive** homogenous relationship between *stock returns and inflation*.

To test the relationship of the real stock return with each type of inflation, we formulate three econometric models. The first model

$$R_t - I_t \cdot \iota = \beta_0 + \beta_1 I_t + \varepsilon_{1t} (7)$$

where $R_t = (RC_t, RI_t)$ and I_t are defined respectively in equation (1)-(2) and (3), and $\iota = (1, 1)$.

The second model, presented the relation between real stock returns and the expected inflation EI_t ,

$$\mathbf{R_{t}} - \mathbf{I_{t}} \cdot \boldsymbol{\iota} = \boldsymbol{\beta}_{0} + \boldsymbol{\beta}_{2} \boldsymbol{E} \boldsymbol{I_{t}} + \boldsymbol{\varepsilon}_{2t}, (8)$$

while, the third model give the relationship between stock returns and unexpected inflations, $U EI_t$,

$$R_t - I_t \cdot \iota = \beta_0 + \beta_3 U E I_t + \varepsilon_{3t}, (9)$$

where β_0 , β_1 , β_2 , and β_3 are 2×1 vectors of real parameters

$$\beta_0 = \begin{pmatrix} \beta_{0I} \\ \beta_{0C} \end{pmatrix}, \beta_1 = \begin{pmatrix} \beta_{1I} \\ \beta_{1C} \end{pmatrix}, \beta_2 = \begin{pmatrix} \beta_{2I} \\ \beta_{2C} \end{pmatrix}, \beta_3 = \begin{pmatrix} \beta_{3I} \\ \beta_{3C} \end{pmatrix},$$

and ε_{t1} , ε_{2t} and ε_{3t} are 2×1 vectors of error terms.

Fisher hypothesis will be *proved* if β_1 , β_2 , and β_3 are respectively equal to *zero* (not significant) in respective regresson (7), (8) and (9).

2. Fama and Schwert approach

In accordance with (Fisher, 1930), (Fama & Schwert, Asset Returns and Inflation, 1977) argued that the *expected nominal return* of an asset is the *expected real return* of the asset plus the *expected inflation* rate (see also (Wohlwend & Goller, 2011)). They developed an approach to determine inflation hedging abilities based on the expected and unexpected inflation as independent variables and the asset return as the dependent variable. After providing the values for expected (EI_t) and unexpected inflation (UEI_t), (Fama & Schwert, Asset Returns and Inflation, 1977) analyzed the inflation hedging abilities with two-factor model. Then the following equation have to be conducted :

$$\begin{pmatrix} {}^{\mathrm{RC}_t} \\ {}^{RI_t} \end{pmatrix} = \begin{pmatrix} \beta_1 \\ \beta'_1 \end{pmatrix} + \begin{pmatrix} \beta_2 \\ \beta'_2 \end{pmatrix} EI_t + \begin{pmatrix} \beta_3 \\ \beta'_3 \end{pmatrix} UEI_t + \varepsilon_t (10)$$

According to the theory of (Fisher, 1930), the beta coefficient for expected inflation $\beta_2(\beta'_2)$ should be equal to one. If $\beta_2(\beta'_2) = 1$, an asset is said to be a *complete hedge* against **expected inflation**. An asset is called a *complete hedge* against **unexpected inflation** if $\beta_3(\beta'_3) = 1$. If $\beta_2 = \beta_3(\beta'_2 = \beta'_3) = 1$, then an asset is said to provide a *complete hedge* against inflation for considered asset.⁵

3. More general models

In this sub-section, we consider effect of real activity on stock market retuns. Real activity is measured by $X_t \equiv RA_t = \Delta \log (IIP_t)$, where IIP_t is the Industrial Production Index. Two specifications are considered for μ_t . In the first one, Inflation and real activity effect mean equation as follow :

$$R_t = \beta_0 + \beta_1 I_t + \beta_2 R A_t + \varepsilon_t, (I)$$

while the second specification suppose that

$$R_t = \beta_0 + \beta_1 I_t + \varepsilon_t$$
(II)

where I_t has also an effect on volatility via parameter λ to be estimated.

B. Volatility patterns

To model the volatility of ε_t , it suffices to consider the **conditional** variances and conditional correlation (CC) coefficients of ε_{it} .⁶

⁵ One would expect all assets to be a complete hedge against expected inflation ($\beta_2 = 1$) but only some assets to provide a complete, if any, hedge against unexpected inflation ($\beta_3 = 1$). ⁶ The mutivariate MGARCH model makes a current conditional variance dependent on lags of its previous variance.

4. Conditional Covariance

The **bivariate** VECH(1, 1) model in full is given by the following system:⁷

$$\begin{cases} \sigma^{2}_{1,t} = \alpha_{1,0} + \alpha_{11}\varepsilon^{2}_{1,t-1} + \alpha_{12}\varepsilon^{2}_{2,t-1} + \alpha_{13}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \beta_{11}\sigma^{2}_{1,t-1} + \beta_{12}\sigma^{2}_{2,t-1} + \beta_{13}\sigma_{12,t-1} \\ \sigma^{2}_{2,t} = \alpha_{2,0} + \alpha_{21}\varepsilon^{2}_{1,t-1} + \alpha_{22}\varepsilon^{2}_{2,t-1} + \alpha_{23}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \beta_{21}\sigma^{2}_{1,t-1} + \beta_{22}\sigma^{2}_{2,t-1} + \beta_{23}\sigma_{12,t-1} \\ \sigma_{12,t} = \alpha_{3,0} + \alpha_{31}\varepsilon^{2}_{1,t-1} + \alpha_{32}\varepsilon^{2}_{2,t-1} + \alpha_{33}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \beta_{31}\sigma^{2}_{1,t-1} + \beta_{32}\sigma^{2}_{2,t-1} + \beta_{33}\sigma_{12,t-1} \\ \sigma_{12,t} = \alpha_{3,0} + \alpha_{31}\varepsilon^{2}_{1,t-1} + \alpha_{32}\varepsilon^{2}_{2,t-1} + \alpha_{33}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \beta_{31}\sigma^{2}_{1,t-1} + \beta_{32}\sigma^{2}_{2,t-1} + \beta_{33}\sigma_{12,t-1} \\ \sigma_{12,t} = \alpha_{3,0} + \alpha_{31}\varepsilon^{2}_{1,t-1} + \alpha_{32}\varepsilon^{2}_{2,t-1} + \alpha_{33}\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \sigma_{12,t} = \alpha_{3,0} + \alpha_{31}\varepsilon^{2}_{1,t-1} + \alpha_{32}\varepsilon^{2}_{2,t-1} + \alpha_{33}\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \sigma_{12,t} = \alpha_{3,0} + \alpha_{31}\varepsilon^{2}_{1,t-1} + \alpha_{32}\varepsilon^{2}_{2,t-1} \\ \sigma_{12,t} = \alpha_{3,0} + \alpha_{31}\varepsilon^{2}_{1,t-1} + \alpha_{32}\varepsilon^{2}_{2,t-1} \\ \sigma_{12,t} = \alpha_{3,0} + \alpha_{31}\varepsilon^{2}_{1,t-1} \\ \sigma_{12,t} = \alpha_{3,0} + \alpha_{3,0}\varepsilon^{2}_{1,t-1} \\ \sigma_{12,t} = \alpha_{3,0} +$$

(Bollerslev, Engle, & Wooldridge, 1988) introduce a restricted version of the general MVECH model of the conditional **variance** and **covariances**. Diagonal VECH(1, 1) model or DVECH(1, 1) model take the following algebric formulation for the **bivariate** DVEC(1, 1) :⁸

$$\begin{cases} \sigma^{2}_{1,t} = \alpha_{1,0} + \alpha_{11} \varepsilon^{2}_{1,t-1} + \beta_{11} \sigma^{2}_{1,t-1} \\ \sigma^{2}_{2,t} = \alpha_{2,0} + \alpha_{22} \varepsilon^{2}_{2,t-1} + \beta_{22} \sigma^{2}_{2,t-1} \\ \sigma_{21,t} = \alpha_{21,0} + \alpha_{21} \varepsilon_{1,t-1} \varepsilon_{2,t-1} + \beta_{21} \sigma_{21,t-1} \end{cases}$$
(12)

where the (α_{ij}) and (β_{ij}) i, j = 1, 2, measure respectively the crossmarket effects of shock spillover and the cross effect of volatility spillover.

5. Conditional Correlation

(Bollerslev, 1990) specifies the elements of the conditional covariance matrix as given by the following system :

$$\sigma_{ij,t} = \rho_{ij,t} \sigma_{i,t} \sigma_{j,t} (13)$$

Where $\sigma^2_{i,t}$ is modeled by the following univariate GARCH process

$$\sigma^2_{i,t} = \alpha_{i,0} + \alpha_{ii} \varepsilon^2_{i,t-1} + \beta_{ii} \sigma^2_{i,t-1}$$

Equation (13) indicate that CC models use nonlinear combinations of univariate GARCH models to represent the conditional covariances and

⁷ For an excellent survey of MGARCH models, see (Bauwens, Laurent, & Rombouts, 2004).

⁸ Where by symetry $\sigma_{21,t} = \sigma_{12,t}$.

that the parameters in the model for $\rho_{ij,t}$ describe the extent to which the errors from equations i and j move together.

To keep the number of volatility equations low, (Bollerslev, 1990) considers the known model as MGARCH constant conditional correlation (CCC): the special case in which the correlation coefficient

 $\rho_{ij,t} = \rho_{ij} \ (14)$ is time-invariant, with $\left|\rho_{ij}\right| < 1.^9$

(Engle R. F., 2002) introduced rather an MGARCH **dynamic conditional correlation** (DCC) model in which the conditional quasicorrelation follow a GARCH(1, 1)-like process ;

 $\rho_{ij,t} = (1 - \theta_1 - \theta_2)\rho_{ij} + \theta_1 a_{t-1} a'_{t-1} + \theta_2 \rho_{ij,t-1}$ (15) where a_t is the standardized innovation vector with elements $a_{it} = \varepsilon_{it} / \sqrt{\sigma^2_{i,t}}$ and θ_1 and θ_2 are non-negative scalar parameters satisfying $0 < \theta_1 + \theta_2 < 1$. The MGARCH - DCC model reduces to the MGARCH - CCC model if $\theta_1 = \theta_2 = 0$ in equation (15).

6. Test for volatility spillovers Effect

Refer to the multivariate volatility model of equation (12) (DVECH), the following hypothesis is of interest to test for volatility spillovers effects across assets. Considering **2 stock market returns**, covariances take the following equation :

$$\sigma_{12,t} = \alpha_{12,0} + \alpha_{12}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \beta_{12}\sigma_{12,t-1},$$

Volatility **Spillovers** from stock 1 to stock 2 can then be tested in the following null hypothesis:

⁹ Under such an assumption, ρ_{ii} is a **constant** parameter.

$$H_0: \ \alpha_{12} = \ \beta_{12} = 0$$

against

 $H_1:\alpha_{12}\neq 0, \quad \beta_{12}\neq 0,$

by applying a **Chi-square** test.

IV. Empirical Results

Twelve regression are estimated with ML method under Student distribution in this section for general model

$$Y_t = X_t \beta + \varepsilon_t,$$

$$\varepsilon_t \sim \text{MGARCH}, t = 1, 2, 3, \dots, T = 165.$$

The following Table give a sum up of different regressions:

Hypothesis and output	Y _t	X _t	Volatility	Model Notation
Fisher	$R_t - I_t \cdot \iota$	It	CCC, DCC	
(Tables 6 and 7	$R_t - I_t \cdot \iota$	EI_t	CCC, DCC, DVECH	X-MGARCH
and Table 8)	$R_t - I_t \cdot \iota$	UEI _t	CCC, DVECH	
Fama- Schwert	D		CCC	<u>У МСАРСИ</u>
(Table 9)	π _t	(E_t, OE_t)		Λ-ΜΟΑΚΟΠ
Model (I)				
(Table 10 and	R_t	(RA_t, I_t)	CCC, DCC	X-MGARCH
Table 11)				
Model (II)	D	I	CCC, DVECH	<u>х мсарси у</u>
(Table 12)	π _t	¹ t	With I_t as regressor	Λ-ΙΨΙΟΑΚΟΠ-Λ

where $R_t = (RC_t, RI_t)$ ', I_t , EI_t , UEI_t , and RA_t are respectively vector of conventional and Islamic return, Inlation, Expected Inflation, Unexpected Inflation, and Real activity at time t. All these variables are defined at section II (or section III). Each Table first presents results for the mean and variance parameters used to model each dependent variable. Subsequently, the output Table presents results for the conditional correlation parameters and then adjustment parameters θ_1 and θ_2 (for DCC case) and student degree of freedom parameter η . Finally, some adequacy criteria are presented as log likelihood (LL) and some information criteria as AIC, BIC, etc.

7. Mean discussion

According to the theory of (Fisher, 1930) presented earlier in this paper, the beta coefficients for Inflation, expected inflation, and unexpected inflation should be **zero** for Canadian assets mean. In order to test the validity of the Fisher's hypothesis, inflation, expected inflation and unexpected inflation has been regressed on real stock return (regressions (7), (8) and (9)). Estimation results for Fisher-MGARCH models by ML under Student distribution are given at Table 6 (for CCC or DCC specification) and Table 7 (for DVECH specification). Looking at **Table 8**, we conclude that CCC error specification is the more adequate model (see Annexe 2) since it has the min of considered information criterion (AIC and BIC). **Table 4** here after represents a sum up of the Fisher and Fama- Schwert hypotheses test results.

From Table 4, **Islamic** canadian stock price is a **complete hedge** against inflation (expected inflation and unexpected inflation) since $H_0: \beta_1 = 0, H_0: \beta_2 = 0$, and $H_0: \beta_3 = 0$ are not rejected (p-values are respectively = 0.090, 0.090, and 0.711 > 5%). Fisher hypothesis is then well *proved* for Islamic canadian stock market. *The Islamic* stock market is then an inefficient market suggesting that information on past values of inflation provides opportunities for abnormal gains from the Islamic canadian stock market.

For **Conventional** canadian stock return, respective coefficients β_1 , β_2 , and β_3 in respective **regressions** (7), (8) and (9) are **significant** (not equal to *zero*), p-values are respectively equal to 0.016, 0.016, and 0.039 < 5%. **Fisher hypothesis** is **not** *proved* for Conventional market. The Conventional stock market is then efficient, it does not provide *a* complete hedge against Inflation. This *efficiency* suggests that

information on past values of inflation could not provides opportunities for abnormal gains from the Conventional canadian stock market.

According to **Fama and Schwert** vision, the beta coefficients for expected and unexpected inflation should be **one** for Canadian assets in **regression** (10). In order to test the validity of the Fama and Schwert's hypothesis, expected inflation and unexpected inflation has been regressed on real stock returns. Estimation results for Fama-Schwert - CCC model by ML under Student distribution are given at Table 9 (see Annexe 3).¹⁰

Looking again at Table 4,¹¹ **Conventional** canadian stock price is rather a hedge against expected and unexpected inflation since $H_0: \beta_2 = \beta_3=1$, is not rejected (p-value = 0.2714). Then **Conventional** canadian stock prices provide a **complete hedge** against inflation. However, **Islamic** canadian stock price **do not provide** a **complete hedge** against expected and unexpected inflation since $H_0: \beta'_2 = \beta'_3=1$ is rejected (p-value = 0.0000).

To conclude about these opposite results, we have to select the more accurate model. Hence, information criterion is in **favor of Fisher hypothesis** results since Fama-Schwert hypothesis results have not the inferior information criterion values.

Table 10 illustrates results by ML under Student distribution of **model** (I) where **inflation and real activity**, $X_t = \Delta \log(\text{IIP}_t)$, are taken as explicative variables with MGARCH (-CCC or -DCC specifications) errors ; see Annexe 4.¹² Diagnostic tests (in **Table 11**; see Annexe 4) suggest adequate specifications as all models show free conditional

¹⁰ See footnote of Table 9 for adequacy discussion of estimated models.

¹¹ Table 4 represents also a sum up of the Fama and Schwert hypothesis test results.

¹² Table 11 gives adequacy question results of these models. All univariate models and multivariate model are adequate (p-value are > 5% level).

heteroskedasticity for residuals. Having lower Information criterion, CCC specification is then the preferable. From Table 10, **real activity** has **significant** effect on **Conventional** return market and has no effect on Islamic return market. While inflation has significant effect for both returns. **Inflation** has less effect on **Conventional** return market.

Table 12 illustrates results by ML under Student distribution of **model** (II) where **inflation** is considered as explicative variable **for** both the mean and the volatility of returns with MGARCH (- CCC or -DVECH specifications) errors; see Annexe 4. Again, information criterion select CCC specification. Looking at Table 12, we conclude that **inflation** has significant effect on both returns with **higher** effect on **Islamic** return market.

FA	MA and S Hypoth		F	ISHER H	ypothe	sis		
$H_0: \beta'_2 = \beta'_3 = 1 \qquad H_0: \beta_2 = \beta_3 = 1$				$H_0: \beta_1=0, H_0: \beta_2=0, H_0: \beta_3=0$				
	RI_t	RC_t		$RI_t - I_t$			$RC_t - I_t$;
			I	EI	UEI	I	EI	UEI
Statistic	1.4e+06	1.21	1.69	1.69	0.37	2.40	2.40	-2.07
P-VALUE	0.0000	0.2714	0.090	0.090	0.711	0.016	0.016	0.039
Reject of								
H ₀	Yes	No	No	No	No	Yes	Yes	Yes

Table 4: Sum up from MGARCH -CCC error specifications results.

8. Volatility discussion

Since by *information criterion* MGARCH-CCC specification for error is the most preferable in all previous investigations, we select the best in these models. Between Model (I) and model (II), information criterion is in favor of model (II). Again, between model (II) and Fisher-MGARCH-CCC specifications, the latter model is preferred with EI_t as regressor. So only this model will be discussed in details.

From Table 6 third column, almost all parameter estimates are significant at the 5% level, and the fitted conditional mean and volatility model is

 $RI_{t} - I_{t} = \mathbf{0.00137651} \ EI_{t} + \varepsilon_{1t},$ $\sigma^{2}_{1,t} = 0.00029635 + \mathbf{0.21258275} \ \varepsilon^{2}_{1,t-1} + \mathbf{0.7321011} \ \sigma^{2}_{1,t-1}, \ 1 \equiv I$

 $RC_t - I_t = 0.0012629 I_t + \varepsilon_{2t}$

 $\sigma^{2}_{2,t} = 0.00004402 + 0.06470915 \varepsilon^{2}_{2,t-1} + \mathbf{0.8974162} \sigma^{2}_{2,t-1}, 2 \equiv \mathbf{C}$

with Constant Conditional Correlations (CCC) $\rho_{(\text{RI-I},\text{RC-I})} = -0.0093597$ is negative but non significant. The Ljung–Box statistics as model checking test is to apply the multivariate *Q*-statistics to the bivariate standardized residual series. For this model, $Q_2(40) = 40.1823$ (0.4622), where the number in parentheses denotes *p*-value. Based on this statistic, the model is then adequate at the 5% significance level.

Only coefficients in **bold** are significant (in 1%, 5% or 10% level). Then, each of the univariate **GARCH** is statistically *significant for both real returns, while* univariate **ARCH** is *significant only for Islamic* stock return. Moreover, the *shot-run* volatility parameters $\alpha_{i,i}$ are inferior than the *long-run* parameters $\beta_{i,i}$ in this model, it implies that the volatility of real return is more affected by the **past volatility** than the related **news** from the previous period. Figure 7 (a) show the fitted **volatilities** of the **Fisher-MGARCH-CCC** model. Comparing these graphs, there are some differences between the fitted volatilities. However, it is clear that **Islamic return is the** *more* **volatil**.¹³

However, by the log likelihood (LL) quantities, MGARCH-DCC specification for error, with EI_t as regressor, is the most preferable in

and

¹³ The same **C Variance** prediction pattern is found from **Fama- Schwert MGARCH(1, 1)** - **CCC** model (see Figure 8 (a) Annexe 3), from **MGARCH(1, 1)** -**CCC** Model (I) (see Figure 9 (a) Annexe 4), from **Fama- Schwert MGARCH(1, 1)** - **DCC** model (see Figure 8 (b) Annexe 3) ; and from **MGARCH(1, 1)** -**DCC** Model (I) (see Figure 9 (b) Annexe 4).

all Fisher investigations. For this model, Ljung–Box $Q_2(40) = 38.6485$ (0.5311), indicating that the MGARCH - DCC model is then adequate at the 5% significance level. Note that, the MGARCH - DCC model reduces to the MGARCH-CCC model if $\theta_1 = \theta_2 = 0$ in equation (15). First, we find the θ_2 coefficient is positively significant. Then, Wald test rejects the null hypothesis that $\theta_1 = \theta_2 = 0$ at all conventional levels since chi2(2) = 9095.41 with p-value = 0.0000. This result indicates that the assumption of *time-invariant conditional correlations* maintained in the MGARCH-CCC model *is too restrictive* for these data. Figure 7 (b) illustrate the Conditionnal *correlation* prediction from Fisher-MGARCH-DCC model with EI_t as regressor. C *Correlation* is negative and decreases from 2004 to 2008, then, it has a stationnary evolution (fluctuates around zero) till 2016, and recently it becomes *increasing positive* till 2018 indicating that the **returns on these stocks rise or fall together.**¹⁴

Since AIC and BIC critiria are minimum for MGARCH-CCC specification, this model is the best but we can not analyse Volatility Spillover for each return with this model. At Table 12, for Model (II) The **X-DVECH-X** results reveal **spillover** *effects* in the volatility models since $\beta_{1,2} \equiv \beta$ (RI, RC) is significant at the 0.01 level. The test results **suggest significant volatility spillovers from Conventional to Islamic stock market** (Chi-square = 28.40336 with p-value = 0.0000). Volatility spillovers from Conventional stock market to Islamic stock market is not due to common news but to the **past volatility**.

Inflation has also significant effect on both returns volatility. From Table 12, model II reveals that inflation has negative (positive) effect on Islamic (conventional) stock return volatility.

¹⁴ The same Conditionnal correlation prediction pattern is found from **MGARCH(1, 1)** -**DCC** Model (I) (see Figure 9 (c) Annexe 4).

V. Conclusion

In this paper, we study the difference between the Conventional and Islamic canadian stock returns. Monthly data covering period from 2004M08 to 2018M04 are taken for analysis. The inflation hedging abilities of stock price are tested using Fisher hypothesis and the (Fama & Schwert, 1977) approach. Information criterion is in **favor of Fisher hypothesis** results, see Table 8 Annexe 2.

With X-MGARCH-CCC, the main result supports Fisher hypotheses that **only Islamic** canadian stock price provides a **complete hedge** against inflation. Then, this **inefficiency** suggests that information on past values of inflation gives opportunities for abnormal gains from the Islamic canadian stock market. While *the Conventional* stock market is an efficient market. This *efficiency* suggests that information on past values of inflation could not provides opportunities for abnormal gains from the Conventional canadian stock market, see Table 4.

From model (I), real activity, $X_t = \Delta \log(\text{IIP}_t)$, is found to have significant effect on Conventional return and have no effect on Islamic return while Inflation has higher effect on Islamic return market, see Table 10 Annexe 4.

In addition, with **Fisher-MGARCH-CCC** model, Islamic return is found to be the *more* volatil, but with **Fisher-MGARCH-DCC** model and from 2016, both stock returns are found to **rise or fall together**, see Figure Figure 7 (b) Annexe 2.

However, from more general models, **real activity** has significant effect only on **Conventional** returns. While **inflation** has significant effect on both returns with **higher** (**lesser**) effect on **Islamic** returns for the first moment (second moment), see Table 10 and Table 12 Annexe 4.

Finally, the X-DVECH-X model reveal spillover *effects* in the volatility from Conventional to Islamic stock market.

Bibliographie

- Aftab, H., Beg, R. A., Sun, S., & Zhou, Z. (2019). Testing and Predicting Volatility Spillover—A Multivariate GJR-GARCH Approach. *Theoretical Economics Letters*, 9, 83-99.
- Bauwens, L., Laurent, S., & Rombouts, J. V. (2004). Multivariate GARCH models: a survey. Journal of Applied Econometrics (to appear).
- Bera, C. (1980). Efficient Tests for Normality, Homoscedasticity and Serial Independence of Regression Residuals. *Economics Letters*, 6, 255-259.
- Bollerslev, T. (1990). Modelling the coherence in short-run nominal exchange rates: A multivariate generalized ARCH model. *Review of Economics and Statistics*, 72, 498– 505..
- Bollerslev, T., & Wooldridge, J. M. (1992). Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time-Varying Covariances. *Econometric Reviews*, 11(2), 143--72.
- Bollerslev, T., Chou, R. Y., & Kroner, K. F. (1992). ARCH Modelling in Finance: A Review of the Theory and Empirical Evidence. *Journal of Econometrics*, *52*(5), 5-59.
- Bollerslev, T., Engle, R. F., & Wooldridge, J. M. (1988). A capital asset pricing model with time-varying covariances. *Journal of Political Economy*, *96*, 116–131.
- Bollerslev, T., Engle, R., & Nelson, D. B. (1994). ARCH Models. Handbook of Econometrics,4,: in R.F. Engle and D. McFadden eds.
- Chatrath, A. R. (1997). Stock prices, inflation and output : evidence from India. *Applied Financial Economics*, *7*, 439-445.
- Enders, W. (2014). Applied Time Series. John Wiley and Sons, Hoboken.
- Engle, R. F. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, 20, 339–350.
- Engle, R. F. (2009). *Anticipating Correlations: A New Paradigm for Risk Management*. Princeton, NJ: Princeton University.
- Engle, R., & Granger, C. (1987). Cointegration and error correction representation : Estimation and testing. *Econometrica*, *55*, 251-276.

- Fama, E. F. (1981). Stock returns, real activity, inflation, and money. *The American Economic Review*.
- Fama, E. F., & Schwert, G. W. (1977). Asset Returns and Inflation. J. Fin. Econ, 5, 115-146.

Fisher, I. (1930). The Theory of Interest. The Macmillan Company.

- Graham, F. C. (1996). Inflation, Real Stock Returns, and Monetary Policy. *Applied Financial Economics*, 6(1), 29-35.
- Neifar, M., & Harzallah, A. (2020). Can Canadian Stock market provide complete hedge against Inflation ? *MPRA_Paper_99033*.
- Samiran, J. (2013). Can Indian stock index return provide a complete hedge against inflation ? International Journal of Research in Management, 1, 96-106.
- Silvennoinen, A., & Terasvirta, T. (2009). *Multivariate GARCH models*. In Handbook of Financial Time Series, ed.
- Wohlwend, R., & Goller, P. (2011). *Finanzanlagen und Inflation*. Vaduz :Liechtensteinische Landesbank AG.

Annexe 1 : Data analysis

Figures



Figure 5: Normality Test for RI and RC



Figure 6: Correlograms for autocorrelations of **RI and RC.**

Tables

Table 1: Descr	ptive statistics	and unit root	tests for Returns.
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	Mean	Median	Max	Min	Std. Dev.	Skewnes s	Kurtosi s	Jarque- Bera	Probabilit y
RC	0.00399	0.009173	0.10982	-0.182673	0.037060	-1.28124	7.74664	198.829	0.000000
RI	0.00292	0.005440	0.22696	-0.361067	0.074736	-0.94111	7.02209	134.753	0.000000
Unit root tests Elliott-Rothenberg- Stock DF-GLS test statistic		Minimize Break Date:	Dickey-Fuller t	-statistic	MZa	Ng-Perro statistics MZt	n test MSB	МРТ	
RC	-1.63540		2008M10	-11.8700*		-3.56368	-1.33122	0.37355	6.87536
<mark>RI</mark> 5% level	-5.1746*		2008M11	-13.3345*		-38.374*	-4.3793*	0.1141*	0.6413*
critical values Conclusion	-1.94283			-4.443649 stationar	V	-8.10000	-1.98000	0.23300	3.17000

Table 2: BDS test results for stock retruns.

	BDS Test for RI						BDS Test for RC				
			Std.	Z-							
Dim		Statistic	Error	Statistic	Prob.	Dim	Statistic	Std. Error	z-Statistic	Prob.	
	2	0.025544	0.006804	3.754058	0.0002	2	0.020924	0.006238	3.354070	0.0008	
	3	0.054650	0.010847	5.038308	0.0000	3	0.041882	0.009931	4.217182	0.0000	
	4	0.071643	0.012957	5.529518	0.0000	4	0.050884	0.011846	4.295630	0.0000	
	5	0.083199	0.013547	6.141626	0.0000	5	0.058376	0.012367	4.720484	0.0000	
	6	0.085008	0.013105	6.486463	0.0000	6	0.062650	0.011945	5.244767	0.0000	

q	RC	RI
1	0.0036	0.000
2	0.000	0.000
3	0.000	0.000
4	0.000	0.001
5	0.000	0.000

Table 3 : Results of **ARCH-LM test** for different values of q.

Note : Only p-value is reported for this test.

Table 4: Unit root tests (ADF and PP) and stationary test (KPSS) for **Returns**.

			UNIT ROOT TEST				
		PP		ADF		KPSS	
		RI	RC	RI	RC	RI	RC
	t-	-					
With Constant	Statistic	11.6052	-10.4691	-4.5809	-5.9069	0.1752	0.0835
	Prob.	0.0000	0.0000	0.0002	0.0000	n0	n0
		***	***	***	***		
Without							
Constant &	t-	-					
Trend	Statistic	11.6264	-10.4285	-4.6039	-7.0050		
	Prob.	0.0000	0.0000	0.0000	0.0000		
		***	***	***	***		

Table 5: Granger Causality test results for returns.

Null Hypothesis:	Obs	F-Statistic	Prob.
RC does not Granger Cause RI	162	230.292	2.E-47
RI does not Granger Cause RC		0.53846	0.5847
Δ LIIP does not Granger Cause RI	162	0.29559	0.7445
RI does not Granger Cause $\Delta\Delta$ LIIP		1.48415	0.2299
I does not Granger Cause RI	162	3.21969	0.0426
RI does not Granger Cause I		3.00665	0.0523
Δ LIIP does not Granger Cause RC RC does not Granger Cause Δ LLIP	162	0.33932 2.35141	0.7128 0.0986
I does not Granger Cause RC	162	0.78764	0.4567
RC does not Granger Cause I		5.20492	0.0065
I does not Granger Cause Δ LIIP Δ LIIP does not Granger Cause I	162	0.78875 0.36830	0.4562 0.6925

Table 0. Fisher - MOARCH -CCC and -DCC specification results.	Table 6: Fisher -	MGARCH	-CCC and	-DCC s	pecification	results.15
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Equation	Equation	(7)	Equation	(8)	Equation	(9)
Variables	CCC	DCC	<mark>CCC</mark>	DCC	CCC	DCC
RI - I I _t	.00137668*	.00137614*				
EIt			.00137651*	.00137602*		
UEI _t					.55052139	.39366967
ARCH_RI - Ι α _{1,1}	.21258153**	.21020292**	.21258275**	.21020298**	.20265586**	.20196872**
$egin{array}{lll} eta_{1,1} \ lpha_{1,0} \end{array}$.7320927*** .00029638	.7270117*** .00032151	.7321011*** .00029635	.7270196*** .00032149	.7382371*** .00028586	.73285221*** .00030882
RC - I I _t	.00126235**	.0013272***				
EI _t UEI _t			.0012629**	.0013277***	-1.818111**	-1.7257859**
ARCH_RC - Ι α _{2,2}	.06470393	.06673348	.06470915	.06673849	.07171588*	.07420855*
$\boldsymbol{\beta}_{2,2}$.8974277***	.8854350***	.8974162***	.8854246***	.8921584***	.88063534***
$\alpha_{2,0}$.00004402	.00005704	.00004402	.00005705	.00004406	.00005637
ρ(ri- i,rc- i)	0093513	.64646239	0093597	.6464291	.02323663	.56625063
η	7.339614**	7.5758918**	7.3392127**	7.5755264**	8.7089381**	8.894904**
θ1		.02226346		.02226429		.01858535
θ₂		.9592875***		.9592864***		.96037731***
ш	556.8422	558.1232	556.8444	558.1254	554.3542	555.4484
AIC	<mark>-1093.684</mark>	-1092.246	-1093.689	-1092.251	<mark>-1088.708</mark>	-1086.897
BIC	<mark>-1062.686</mark>	-1055.048	-1062.69	-1055.052	<mark>-1057.71</mark>	-1049.698

¹⁵ This is done by Stata 15.

		EI _t 17		UEI _t ¹⁸		
		DVECH		•	<mark>DVECH</mark>	
	Coefficient	Std. Error	Prob.	Coefficient	Std. Error	Prob.
β_{jI}	0.001248	0.000817	0.1268	0.388120	1.899025	0.8381
β_{jC}	0.001248	0.000538	<mark>0.0204</mark>	-2.015991	1.192086	0.0908
a	0 000115	0 705 05	0 0077	0.0004.00	0 000110	0.0005
u ₀	0.000115	9.73E-05	0.2377	0.000126	0.000113	0.2665
u ₁₁ 0	0.215526	0.088144	0.0145	0.208740	0.085833	0.0150
P ₁₁	0.782989	0.073041	0.0000	0.782425	0.076506	0.0000
α_{22}	0.088262	0.078280	0.2595	0.105625	0.086859	0.2240
β_{22}	0.821171	0.127118	0.0000	0.799789	0.146208	0.0000
<i>α</i> ₁₂	0.056120	0.078935	0.4771	0.054411	0.118136	0.6451
β ₁₂	-0.880350	0.224827	0.0001	-0.023427	1.551557	0.9880
η	7.620043	2.425751	0.0017	8.554190	2.775277	0.0021
Log likelihood			556.6003			554.0172
Avg. log likelihood		1.696952			1.689077	
Akaike info criterion		-6.665858 ¹⁹			-6.634357 ²⁰	
Schwarz criterion		-6.476842			<mark>-6.445340</mark>	
Hannan-Quini	n					
criterion.			-6.589124			-6.557623

Table 7 (suite Table 6): Fisher MGARCH -DVECH model results.¹⁶

Note : Results for Inflation is the same as for expected inflation so it is omitted from the table.

¹⁶ This is done by Eviews 10. Note : Islamic=I=1 and Conventional=C=2.

¹⁷ j=2

¹⁸ j=3

¹⁹ With stata, AIC= -1092.011 and BIC= -1054.812.

 $^{^{20}}$ With stata, AIC= -1091.662 and BIC= -1048.264

Model	Obs	ш	df	AIC	BIC
I _t _CCC	164	556.8422	10	<mark>-1093.684</mark>	<mark>-1062.686</mark>
I _t _DCC	164	<mark>558.1232</mark>	12	-1092.246	-1055.048
I _t _DVECH	164	558.0031	12	-1092.006	-1054.808
EI _t _CCC	164	556.8444	10	- <mark>1093.689</mark>	<mark>-1062.69</mark>
EI_t_DCC	164	<mark>558.1254</mark>	12	-1092.251	-1055.052
EI_t_DVECH	164	558.0054	12	-1092.011	-1054.812
UEI _t _CCC	164	554.3542	10	-1088.708	<mark>-1057.71</mark>
UEI _t DCC	164	<mark>555.4484</mark>	12	-1086.897	-1049.698
UEI _t DVECH	164	554.0172	12	-1091.662	-1048.264
ι					

Table 8: Information criterion for model adequacy of different Fisher-MGARCH specifications.²¹



Figure 7 (a): C Variance prediction from Fisher MGARCH(1, 1) -CCC model with EI_t.



Figure 7 (b): C Correlation prediction from Fisher MGARCH(1, 1) -DCC model with EI_t.

²¹ This is done by Stata 15.

Annexe 3: Fama - Schwert hypothesis results

		Robust		
	Coef.	Std. Err.	Z	P> z
Ri				
EIt	.0012389	.0008558	1.45	0.148
UEI _t	1.389339	1.541278	0.90	0.367
ARCH_Ri				
$\alpha_{1,1}$.2326704	.0885912	2.63	0.009
$eta_{1,1}$.7192413	.0558175	12.89	0.000
$\alpha_{1,0}$.0003214	.0002687	1.20	0.232
Rc				
EIt	.0013401	.0005079	2.64	<mark>0.008</mark>
UEI _t	8605693	.7837253	-1.10	0.272
ARCH_Rc				
α _{2,2}	.1534841	.0802669	1.91	0.056
$\beta_{2,2}$.7933262	.0760011	10.44	0.000
α _{2,0}	.0000724	.0000435	1.66	0.096
ρ (Ri,Rc)	.1293579	.076977	1.68	<mark>0.093</mark>
df				
η	7.636502	3.230339	2.36	0.018
LL				552.3723
AIC				<mark>-1080.745</mark>
BIC				<mark>-1043.546</mark>

Table 9: Fama - Schwert MGARCH(1, 1) - CCC specification results.²²

Note : LL : log likelihood.

²² This is done by Stata 15. Univariate and multivariate **Ljung-Box test** results for adequacy of model **MGARCH(1, 1)** -CCC and -DCC are given in the following table (same result). Adequacy is prouved at 1% level.

	Portmanteau (Q)	Prob > chi2(40)
	statistic	
RC	58.2258	0.0312
RI	46.3688	0.2263
MULTI	58.2258	0.0312

		Robust			
	Coef.	Std. Err.	Z	P> z	
Ri					
Eli	1113263	.0672598	-1.66	<mark>0.098</mark>	
UEli	1.650565	1.504642	1.10	0.273	
_cons	.5236825	.3130437	1.67	0.094	
ARCH_Ri					
$\alpha_{1,1}$.2050302	.0822214	2.49	0.013	
$eta_{1,1}$.7239349	.0575125	12.59	0.000	
$\alpha_{1,0}$.0004062	.0002832	1.43	0.151	
Rc					
Eli	0541989	.0342834	-1.58	0.114	
UEli	6713398	.7777966	-0.86	0.388	
_cons	.2580794	.1598057	1.61	0.106	
ARCH_Rc					
α _{2,2}	.1244083	.0676566	1.84	0.066	
$\beta_{2,2}$.8128555	.074276	10.94	0.000	
<i>α</i> _{2,0}	.0000812	.000051	1.59	0.111	
ρ (Ri,Rc)	.9099644	2.397274	0.38	<mark>0.704</mark>	
Adjustment					
$oldsymbol{ heta}_1$.0508369	.0351547	1.45	0.148	
θ_2	.9418227	.0230215	40.91	<mark>0.000</mark>	
df					
η	6.850905	2.593885	2.64	0.008	
LL		<mark>555.8989</mark>			
AIC				-1079.798	
BIC				-1030.2	

Table 9 (suite) : Fama - Schwert MGARCH(1, 1) - DCC specification results.

Note : LL : log likelihood.



Figure 8 (a): C Variance prediction from Fama- Schwert MGARCH(1, 1) - CCC model



Figure 8 (b): C Variance prediction from Fama- Schwert MGARCH(1, 1) - DCC model

Annexe 4 : More general models results

Variable	ccc	DCC
RC		
Δ LCPI	1.7525437***	1.8646155***
Δ LIIP	<mark>.06917368</mark> **	.06928065**
$\alpha_{ m RC,1}$.09923731	.09211448
$\beta_{ m RC,1}$.86280186***	.86113732***
$\alpha_{ m RC,0}$.0000459	.00005709
RI		
Δ LCPI	2.5505387**	2.7749739***
Δ LIIP	<mark>04758217</mark>	0522488
$\alpha_{\rm RI,1}$.22308379***	.21406085***
$\boldsymbol{\beta}_{\mathrm{RI},1}$.72117146***	.71826289***
$\alpha_{ m RI,0}$.00032827	.00037696
$ ho_{(ext{Rc,Ri})}$.10709871	2.007076
η	7.3432047***	7.4042929***
θ_1		.04933385
θ_2		<mark>.94637979***</mark>
AIC	<mark>-1085.674</mark>	-1084.617
BIC	- <mark>1048.476</mark>	-1041.219
LL	554.8371	<mark>556.3087</mark>

Table 10: MGARCH(1, 1) - CCC and -DCC results of models (I).²³

Note : LL : log likelihood.

²³ This is done by Stata 15.

	ССС			DCC		
	RC	RI	Multivar	RC	RI	Multivar
Portmanteau ((LB-Q))						
statistic	55.6705	47.1232	55.6705	55.4479	47.4082	55.4479
Prob > chi2(40)	0.0508	0.2041	0.0508	0.0529	0.1961	0.0529

Table 11 : Univariate and multivariate **Ljung-Box test** for model (I) adequacy.

Table 12: MGARCH(1, 1) - CCC or -DVECH results of Model (II).²⁴

	CCC				DVECH		
		Robust				Robust	_
	Coefficient	Std. Error	Prob.		Coefficient	Std. Error	Prob.
β (RI)	2.917778	1.227302	<mark>0.0174</mark>		2.412152	1.407410	0.0865
β (RC)	1.471781	0.615747	<mark>0.0168</mark>		1.366362	0.618637	0.0272
	Variance Ed	quation Coef	ficients		Variance Eo	quation Coef	ficients
$\alpha_{0,RI}$	0.001397	0.000529	0.0083		-1.84E-05	2.87E-05	0.5203
α (RI,RI)	0.221541	0.099222	0.0256		0.097834	0.021532	0.0000
β (RI,RI)	0.547173	0.179449	0.0023		0.898551	0.014983	0.0000
$\alpha_{0,RC}$	-3.06E-05	3.11E-05	0.3259		-1.84E-05	2.87E-05	0.5203
<i>α</i> (RC,RC)	0.086565	0.037848	0.0222		0.110303	0.047424	0.0200
β (RC,RC)	0.886632	0.051058	0.0000		0.859316	0.056193	0.0000
a (RI,RC)					0.007800	0.061651	0.8993
β (RI,RC)					0.784022	0.151122	<mark>0.0000</mark>
$ ho_{(m RC,RI)}$	0.092318	0.089727	<mark>0.3035</mark>				
λ(RI,RI)	-0.173813	0.102170	<mark>0.0889</mark>	λ	0.042187	0.014145	0.0029
λ (RC,RC)	0.043783	0.016152	<mark>0.0067</mark>				
Log likeliho	od		<mark>550.1417</mark>				547.0879
Akaike info	criterion		-6.574899 ²⁵				-6.549853
Schwarz criterion		<mark>-6.366982</mark>				-6.360837	
Hannan-Qu	inn						
criterion.			<mark>-6.490493</mark>				-6.473120

Note : LL : log likelihood.

²⁴ This is done by Eviews 10.

 $^{^{25}}$ With stata, we obtain AIC= -1086.791 and BIC= -1049.592.



Figure 9 (a): Time-varying covariances from MGARCH(1, 1) -CCC Model (I)



Figure 9 (b): Time-varying covariances from MGARCH(1, 1) -DCC model (I)



Figure 9 (c) : Time-varying correlations from MGARCH(1, 1) -DCC model (I)



Figure 10 : Time-varying covariances from MGARCH(1, 1) - CCC model (II)