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Empirical Evidence on the Relationship between Stock market returns and Macroeconomic variables: Panel VAR approach

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Abstract

This study sought to examine the interaction between interest rate, monetary aggregate (M1), exchange rate, inflation, foreign direct investment and stock market return in two emerging countries namely, Mexico and Brazil and two developed countries namely, Denmark and Japan. The study determined the response of the stock returns to a shock in each of the macroeconomic variables. The Panel VAR approach is used to establish the relationship between stock returns and the macroeconomic variables. Empirical results of the regression model revealed that foreign direct investment showed a significant relationship with stock returns in emerging countries. In developed countries, macroeconomic variables showed a no significant relationship with stock returns. IRF observation shows that for emerging countries the interest rate, the inflation rate and the FDI response on stock prices is positive and significant over the short run and long run. However, exchange rate responses negatively and significantly to stock prices during a short period. We note that the monetary aggregate response to stock prices is negative and significant during a long period. For developed countries, the major of macroeconomic factors response on stock prices is constant and stable.

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1 Introduction

In emerging and developed countries, investors have a great interest in discovering variables that may help forecast stock prices. Policymakers pay attention to the situation of the stock market that can be regarded as a leading indicator of future macroeconomic activity. The interaction between macroeconomic variables and stock market has been subjected to serious economic research. In the theory, stock market played a prominent role in shaping a country's economic and political development.

In the economic theory, there is no unified opinion on the relationship between stock returns and inflation. Fisher (1930) argues that inflation causes an increase in the nominal stock return. Bodie (1976) suggest that stock investment acts as an effective hedge against inflation. Moreover, some authors argument the presence of negative relationship between inflation and stock prices. An increase in inflation will result in high money supply. When the money in circulation decreases, demand remaining the same nominal interest rate will rise. An increase in discount rate will result in a decrease in stock prices. Inflation is measured in term of GDP deflator and consumer price index (CPI). Some authors using consumer price index to measure inflation rate. CPI measures changes in the prices of basket of consumer goods in a given time period.

A negative relationship between inflation and stock prices is discussed in the literature because an inflation rate increase is accompanied by a lower expected earnings growth and higher required real yields. A theoretical explanation was given by the literature concerning the negative relation between inflation and stock market prices. Central banks objective is prices stability, thus they control for the inflation level. Inflation indicator increase (decrease) (Consumer Price Index for example) causes a rise (decline) in the anticipated real inflation. Pearce and Roley (1985) show that this is a political restrictive sign by the central bank. So the inflation rate level increase involves a restrictive monetary policy, allowing increasing future cash-flows discount rate but do not act directly on the latter.

The relationship between money supply and stock prices is documented by many studies. Increased nominal money supply results in a portfolio rebalancing. An increase in demand for equity shares will result in a rise in stock prices. Bernanke and Kuttner (2005) suggest that a rise in the discount rate decreases the present value of the future cash flows on the investment and results in a drop in the stock prices. In this study, we use M1 as proxy for money supply which is considered as narrow money which consists of currency plus demand deposits.

Interaction between foreign exchange market and stock market is analyzed through two theoretical approaches: the "stock oriented" approach (e.g. Branson, 1983; Frankel, 1983) and the "flow oriented" approach (e.g. Dornbush and Fisher, 1980). In the first approach, the foreign exchange rate is determined by the demand and supply of financial assets such as equities and bonds. In the second approach, the exchange rate is determined by a country's current account balance or trade balance. Flow oriented models provides a positive interaction between stock price and foreign exchange rate.

In the literature, a positive relationship between the stock prices and exchange rate may result from a real interest rate disturbance as the real interest rises, the exchange rate falls and the capital inflow increases (Wu, 2000).

In the literature, it is suggested that macroeconomic fundamentals act on stock market prices. Asprem (1989) demonstrates that interest rate variations have considerable impact on the discount rate through their effects on the risk free nominal rate. Consequently, when the interest rate increases investors incur capital losses and leave the equity market. Interest rate exercises an impact on firm's operations. Indeed, any interest rates increase causes capital losses amplification, consequently the firm has to exercise labor force to generate higher yields in high interest rates environment. Otherwise interest expenditure related to inflation destroys profits. If the interest rates increase that the firm cannot pay off its debt, the survival of this company will be endangered. In this case, investors will ask for even higher risk premium. Consequently, the fair value will fall even more.

The interest rate increase raises domestic securities yields denominated in national currency. Arbitrage is favorable to buy domestic securities. In the foreign exchange market, there would be an excess of national currency demand. Thus, national currency appreciation means a depreciation of the foreign currency. The national currency appreciation increases foreign investor's return denominated in national currency and is FDI attractiveness. When national currency is devaluated, exportations increase and the company's profit and revenue will rise and its stock market value will appreciate. Finally, interest rate increase leads to the national currency appreciation and lower equity prices.

The empirical evidence on the stock price – macroeconomic variable relationships has been document by numerous studies. For example, Spyrou (2004) examined the interaction between stock return and inflation for 10 selected emerging markets. For Mexico, he found that the relationship was insignificant during 1989M1–1995M12, 1989M1–2000M8, and 1995M12–2000M6. Husain (2006) examine the causal relationship stock market prices and Pakistani real sector by using annual data from 1959-1960 to 2004-2005. He found a causal relation between variables with several econometric techniques such as ECM, Engle and Granger cointegration, ADF and the unit root tests. These researches indicate the presence of long-run relationship between the stock prices and real sector variables.

Abugri (2008) use a the VAR model to analyzed the effect of macroeconomic variables on stock prices for four Latin American countries. For Mexico, the stock return is negatively affected by the U.S. Treasury bill rate, industrial production, money supply, domestic interest rate and the exchange rate. Moreover, the stock return is positively affected by the MSCI world stock index. In the other hand, Adam and Tweneboah (2008) used Johansen's Multivariate cointegration approach for Ghana and analyzed the interaction between some economic indicators and stock prices by selecting the period from 1991 to 2006. The findings of Impulse Response Function (IRF) demonstrated that Foreign Direct Investment and interest rate were the major estimators of the stock index in Ghana.

Rahman, et al., (2009) used the VAR/VECM framework and explored the interaction between selected macroeconomic variables and stock prices for the case of Malaysia. They found that changes in Malaysia stock market index do perform a cointegrating relationship with changes in interest rate, exchange rate, money supply, reserves and industrial production index. Aloui and Jammazi (2009) combine a wavelet analysis and markov regime-switching models (MS-VAR) and prove that the stock market reaction of three developed countries like France, Japan and UK to shocks affecting oil prices is asymmetric. In US, Odusami (2009) shows that oil price unexpected chocks have an asymmetric and non linear impact on stock returns.

More recently, Mohd Hussin, et al., (2012) using the VECM methodology to examine the relationship between the development of Islamic stock market and macroeconomic variables in Malaysia. Their findings showed that Islamic stock price is negatively related with exchange rates and money supply and significantly and positively related with Consumer Price Index and Industrial production Index.

In the other hand, Pierdzioch and Kizys (2012) compared the linkages between the stock markets in three NAFTA countries, namely, the U.S., Mexico and Canada based on the fundamentals and speculative bubbles. They showed that the fundamentals have stronger effects on stock prices than the speculative bubbles. P.Bhannu Sirresha (2013) use linear regression technique and investigated the effect of selected macroeconomic factors on the movements of the Indian stock market, Nifty including gold and silver prices. He found an interdependent relationship between the returns on stock, gold commodities and silver commodities.

Yu Hsing (2014) explored the interaction between the Estonian stock market and some macroeconomic factors and found that the index is positively affected by real gross domestic product, the debt to GDP ratio and the stock market index in Germany. However, the index is negatively associated with the borrowing Interest rates, the expected rate of inflation, the domestic lending and the exchange rate.

Cyrus M, Kirwa L (2015) using co integration and vector autoregressive and investigated the dynamic relationship between major macroeconomic variables in Kenya and stock prices. Positive relationships were found between the Nairobi share prices (NSE), Treasury bill rate (TBR) and GDP exchange rate. However, authors found a negative relationship between consumer price index (CPI) and

NSE performance.

This study examines the relationship between stock price and macroeconomic variables in four emerging and developed countries namely, Mexico, Brazil, Denmark and Japan. It also analyses the theoretical relationship that exist between stock market volatility and macroeconomic variables for the period ranging from 1995 to 2015.

2 Econometric methodology

2.1 Panel VAR modeling

The VAR models are often used in finance and in Applied Economics. In VAR models, all variables are considered to be endogenous and interdependent, at the same time in a dynamic or static sense. Furthermore, exogenous variables may be included in the VAR modeling structure (see Ramey and Shapiro, 1998).

We have X_t a vector of endogenous variables with nx1 dimension. The VAR model of X_t is as follows:

$$X_t = A_0(t) + A(L)X_{t-1} + \varepsilon_t \tag{1}$$

where $\varepsilon_t \sim iid(0, \Sigma_\varepsilon)$

A(L) is a lag polynomial and iid means independent and identically distributed. Restrictions are generally imposed on the Aj matrix coefficients to delimit the Xt variance and ensuring the existing of $A(L)^{-1}$. Often, the equation (1) is decomposed to its short run and long run components. (Beveridge and Nelson (1981) and Blanchard and Quah (1989), among others).

Noting that $A_0(t)$ includes all the data determinist components. Thus, the specification (1) can include constants, seasonal dummy variables and time varying determinist polynomial.

A modification of the equation (1) allows to the n variables Xt to be a linear function of an exogenous variables set Yt (predetermined). In this case, the VAR model is rewritten as follows:

$$X_t = A_0(t) + A(L)X_{t-1} + F(L)Y_t + \varepsilon_t \tag{2}$$

Such a modified structural VAR or VARX was described by Ocampo and Rodriguez (2011) and used in their analysis by, for example, by Cushman and Zha (1997) of the monetary policy effects in Canada.

VAR models with a finite order and fixed coefficients described by the equation (1) could be derived by several ways. The first standard way is by using of Wold theorem (Canova, 2007) and supposing the linearity, time invariance and the irreversibility of the resulting moving average representation. Under these assumptions, there exists a $\mathrm{VAR}(\infty)$ representation for every vector of variables Xt. To truncate the VAR model infinite dimension and use a p order VAR finite and weak, in the empirical analysis, we suppose that the Xt-j contribution in the explanation of Xt is weak when j is high.

The Panel VAR models have the same structure of standards VAR models, when all the variables are supposed to be endogenous and interdependent, but a cross-sectional is added to the VAR representation.

If Xt is the amplified version of xi,t , the n variables for every individual I (i=1, .., n), meaning $x_t = (x_{1t}, x_{2t}, \dots x_{nt})'$. The index i is generic and can indicate countries, sectors, markets, banks or a combination among them. Then, the Panel VAR model is given by the following equation:

$$x_{it} = A_{0i}(t) + A_i(L)X_{t-1} + \varepsilon_{it}, \qquad \forall i = 1, \dots, n; t = 1, \dots, T \tag{3}$$

Where ε_{it} is an nx1 vector of the errors terms; $A_{0i}(t)$ and A_i can depending from the cross-sectional component i. When a Panel VARX is considered, the representation is:

$$x_{it} = A_{0i}(t) + A_i(L)X_{t-1} + F_i(L)Y_t + \varepsilon_{it} \tag{4}$$

Where $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \dots, \varepsilon_{nt})' \sim \mathrm{iid}(0, \Sigma)$, F_{ij} are n x m matrix for every lag $j = 1, \dots, q$ and Y_t is a vector of exogenous variables common for all the i individuals.

A simple inspection of the equations (3) and (4) suggests that a Panel VAR had three main characteristics. First, the lags of all the endogenous variables for all the individuals inter into the model for the individual i. this characteristic is called "dynamic interdependency". Second, the errors ε_{it} are generally corrolated through the individuals i and this characteristic is called "static interdependency". Third, the chocks ε_{it} constant, slope and variance are specific to the individual. This characteristic is called "cross-sectional heterogeneity".

These characteristics allow distinguishing a Panel VAR model, typically used in macroeconomic studies from Panel VAR model used in microeconomic studies. (Eakin and al. 1988 ; Vidangos, 2009 ; Benetrix and Lane, 2009 and Beetsma and Giuliadori, 2011 ; among others).

2.2. Unit root tests for Panel data

2.2.1 Im, Pesaran et Shin Test (2003)

Im and al. (1997) propose t-bar statistic based on the mean of individual ADF statistics to investigate the Panel data unit root assumption. The authors claim that their t-bar statistic has a more precise size and higher power than the data Panel unit root test of Levin and Lim (1993), taking into account residuals heterogeneity and serial correlation through groups. For a sample of n observed groups over a period t, the unit root regression of the conventional ADF test data Panel is given by:

$$\Delta Y_{it} = \alpha_i + \beta_i Y_{it-1} + \sum_{j=1}^{p_i} \gamma_{ij}\, \Delta Y_{it-j} + \varepsilon_{it} \quad \forall\, i = 1 \ldots n \qquad \text{and} \qquad \forall\, t = 1, \ldots, T \quad (5)$$

Where Y_{it} is the study variable for the country i during the period t. Δ denotes the first difference operator. ;α_i, β_i and γ_{ij} are the coefficients to be estimated and ε_{it} is the error term. Im and al. (1997) propose to test the null assumption of data Panel unit root as follows:

$$\begin{cases} H_0 : \beta_i = 0 \; \forall\, i \\ H_1 : \beta_i < 0 \; \forall\, i = 1,2, \ldots, N_1 \text{ et } \forall\, i = N_1 + 1, N_2 + 2, \ldots, N \end{cases}$$

The equation relative to the alternative assumption allows to the coefficient β_i to differ from groups and is more general than the homogenous alternative assumption such: $\beta_i = \beta < 0 \; \forall\, i.$ Im and al. (1997) propose a standard t-bar statistic $(\psi_{\bar{t}})$ given by:

$$\psi_{\bar{t}} = \frac{\sqrt{n}\{\bar{t}_{nT} - (1/n) \sum_{i=1}^{n} E[t_{i,T}(p_i, 0) | \beta_i = 0]}{\sqrt{1/n \sum_{i=1}^{n} \mathrm{Var}\, [t_{i,T}(p_i, 0) | \beta_i = 0]}} \qquad (6)$$

Where $\bar{t}_{nT} = \frac{1}{N} \sum_{i=1}^{n} t_{i,T}\ (p_i,\ \beta_i)$ and $t_{i,T}(p_i,\ \beta_i)$ is the individual t statistic to test the null assumption $\beta_i = 0 \forall\, i$. Noting that: $E[t_{i,T}(p_i, 0) | \beta_i = 0]$ et $\mathrm{Var}[t_{i,T}(p_i, 0) | \beta_i = 0]$ are reported in table (2) of Im and al. (1997). Since $[t_{i,T}(p_i, 0) | \beta_i = 0]$ and $\mathrm{Var}[t_{i,T}(p_i, 0) | \beta_i = 0]$ vary when ADF regression lag length vary. In practice, we use the same lag length in all the individual ADF regressions. Under the null assumption, the standardized statistic $\psi_{\bar{t}}$ is asymptotically standard distributed $(\psi_{\bar{t}} \sim N(0,1))$.

Im and al. (1997) used a Monte Carlo simulation and find best performance of finite samples for the statistic $\psi_{\bar{t}}$ compared to the Levin and Lin test (1993). If the variables are characterized by common trends, the individual ADF regression errors could be simultaneously correlated. The error term ε_{it} is supposed to be composed by two random components:

$$\varepsilon_{it} = \theta_t + \vartheta_{it} \qquad (7)$$

With θ_t a common specific individual and stationary effect taking into account one dependence degree between groups. ϑ_{it}represents an idiosyncratic (specific) random effect independently distributed between groups. According to Im and al. (1997) simultaneous correlations of errors from individual ADF regressions can affect the critical values and the power of data Panel unit root tests.

2.2.2 Madalla and Wu Test (1999)

The Fisher test P_{λ} developed by Madalla and Wu (1999) enhanced the P-values of ρ_i from the ADF regression for each one of the n ADF regressions for ρ_i issued from the following equation :

$$\Delta Y_{it} = \alpha_i + \beta_i Y_{it-1} + \sum_{j=1}^{p_i} \gamma_{ij}\, \Delta Y_{it-j} + \varepsilon_{it} \forall\, i = 1 \dots n \text{ and } \forall\, t = 1, \dots, T \tag{8}$$

The first order autoregression correlations and has Madella and Wu (1999) test is non parametric and is based on the Fisher's work (1932). Furthermore, this test is similar to the Im and al. (2003) test because it takes into account the different the same assumptions (null and alternative) in the estimation procedure. The Fisher test statistic $(P(\lambda))$ is given as follow:

$$P(\lambda) = -2\sum_{i=1}^{n} \ln(\pi_i) \tag{9}$$

Where π_i is the test statistic P-value for the individual i. The Fisher test statistic $P(\lambda)$ follows a $\chi^2(2n)$ statistic low. Maddala and Wu (1999) show that the Fisher test type has a more precise size and higher power comparing to the test of Levin and Lim (1993). The Fisher test advantage is that it allows the use of the different lags in the individual ADF regressions, although the Im and al. (2003) test requires the same individual regressions lag length.

According to Banergie (1999) and Maddala and Wu (1999), the Fisher test is very useful in practice since it reduces bias caused by the optimal lag selection procedure. Furthermore, there are three other statistics used to test the null assumption stipulating that each Panel contains unit roots.

$$Z = \frac{1}{\sqrt{N}}\sum_{i=1}^{N} \Phi^{-1}(p_i) \rightarrow N(0,1) \tag{10}$$

Where $\Phi^{-1}(.)$ the inverse of the standard normal function distribution.

$$L^{*} = \sqrt{\frac{3(5N+4)}{\pi^2 N(5N+2)}}\sum_{i=1}^{N} \ln\left(\frac{p_i}{1-p_i}\right) \rightarrow t(5n+4) \tag{11}$$

Under the null assumption, if $T \rightarrow \infty$ then by $N \rightarrow \infty$, the statistic P tends towards infinity. Thus, Choi (2001a) proposed a modified χ^2 statistic, noted P_m, which converges to a standard normal distribution ((N(0,1)).

$$P_m = -\frac{1}{\sqrt{N}}\sum_{i=1}^{N}[\ln(p_i)+1] \rightarrow N(0,1) \tag{12}$$

3 Data and preliminary analyses

In this paper, we study the interaction links between the stock returns and macroeconomic variables. We estimate a VAR model with Panel data context to study the shock effects of every macroeconomic fundamentals on stock returns while considering two groups of heterogeneous countries: emerging and developed namely, Mexico, Brazil, Japan and Denmark. We consider the raw nominal exchange rates series, market prices and macroeconomic fundamentals with quarterly frequency (81 observations) from 1995:Q1 to 2015:Q1.

Table 1, 2, 3 and 4 report Maddala and Wu (1999) and Im and al. (2003) unit root results. For the two tests, null hypothesis rejection indicates that the tested variables are stationary.

In our empirical analysis, we adopt the model with original and demeaned data. For the IPS test, the common lag is chosen on the basis of SBIC criterion. For the Fisher test, the lag size is chosen with the SBIC criterion and is equal to individual ADF regressions. First, we apply the IPS test and Fisher test on the original series. Tables (1) and (2) present Panel data unit root tests of the original series. We report four statistics of the IPS test: t-bar, t-tilde-bar, Z-t-bar and W-t-bar based on the ADF statistics.

Moreover, we report four statistics of the Fisher test: P, Z, L* and Pm. From these tables, we note that the unit root null assumption can be rejected in most series at a 1%, 5% and 10% significant level.

Second, we use demeaned data to reduce contemporaneous correlation and then apply IPS and Fisher tests to demeaned data series. Im and al. (2003) suggest that error contemporaneous correlations from individual ADF regressions can affect Panel data unit root tests power. Tables (3) and (4) present Panel data unit root tests of demeaned series. Using the IPS test statistics, we can reject the unit root null assumption at a 1%, 5% and 10% significant level. Furthermore, using the Fisher test statistics, we can reject also the unit root null assumption at 5% significant level.

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Table1. Original data for emerging countries

	Fisher-type tests							
Variables	Fisher-ADF statistic				Fisher-PP statistic			
	P	Z	L*	Pm	P	Z	L*	Pm
stock price	7.8196	-1.2985	-1.3303	1.3504	1.9992	1.0225	1.0892	-0.7074
(p-value)	-0.0984	-0.0971	-0.1023	-0.0884	-0.7359	-0.8467	-0.8528	-0.7603
stock return	81.7876	-8.4183	-16.5934	27.5021	115.8892	-10.138	-23.512	39.5588
(p-value)	0	0	0	0	0	0	0	0
IDE	107.888	-9.802	-21.8887	36.7299	130.1848	-10.8604	-26.4123	44.6131
(p-value)	0	0	0	0	0	0	0	0
exchange rate	25.8251	-4.1506	-5.2373	7.7163	13.9251	-2.6312	-2.7966	3.5091
(p-value)	0	0	-0.0001	0	-0.0075	-0.0043	-0.0071	-0.0002
interest rate	9.1542	-1.6585	-1.6983	1.8223	2.3714	0.3542	0.3376	-0.5758
(p-value)	-0.0574	-0.0486	-0.0558	-0.0342	-0.0678	-0.0384	-0.0297	-0.0176
M1	0.5578	3.3521	4.7417	-1.217	0.0022	3.0556	4.0023	-1.4134
(p-value)	-0.9676	-0.9996	-0.9998	-0.8882	-1	-0.9989	-0.9985	-0.9212
Ln(M1)	25.1809	-3.7298	-5.0674	7.4886	74.1904	-6.0195	-14.8776	24.8161
(p-value)	0	-0.0001	-0.0001	0	0	0	0	0
IPC	16.324	-2.9621	-3.2907	4.3572	8.6715	-1.3959	-1.4835	1.6516
(p-value)	-0.1026	-0.1015	-0.1027	0	-0.1699	-0.1814	-0.1801	-0.1493
Ln(IPC)	77.9595	-8.1896	-15.8167	26.1486	105.1789	-9.6706	-21.3391	35.7722
(p-value)	0	0	0	0	0	0	0	0

Notes: The t-tilde-bar ($\tilde{\mathbf{t}} - \mathbf{bar_{NT}}$) statistic is similar to the t-bar$(\mathbf{t} - \mathbf{bar_{NT}})$, statistic except a different error variance estimator of the Dickey-Fuller regression is used. A standardised version of the statistic t-tilde-bar is $-\mathbf{t} - \mathbf{tilde} - \mathbf{bar}(\mathbf{Z_{\tilde{t}-bar}})$. In presence of serial correlation, Dickey-Fuller regression is augmented as follow : $\Delta \mathbf{y_{it}} = \boldsymbol{\phi}_\mathbf{i} \mathbf{y_{i,t-1}} + \mathbf{z'_{it}} \boldsymbol{\gamma}_\mathbf{i} + \sum_{\mathbf{j=1}}^{\mathbf{p}} \Delta \mathbf{y_{i,t-j}} + \boldsymbol{\epsilon}_\mathbf{i,t}$ where $\mathbf{p}$ is the number of lags. Im et al. (2003) propose thus another statistic noted $\mathbf{W_{t-bar}}$ which follows an asymptotical standard normal distribution when $\mathbf{T} \rightarrow \infty$ followed by $\mathbf{N} \rightarrow \infty$.

Table 1: (continued)

IPS test			
t-bar	t-tilde-bar	Z-t-tilde-bar	W-t-bar
-0.8364	-0.8238	1.1551	1.1263
-0.876	-0.876	-0.876	-0.87
-8.355	-6.0615	-7.8779	-10.7463
0	0	0	0
-8.9766	-6.3268	-8.3332	-8.6966
0	0	0	0
-3.1399	-2.977	-2.5574	-3.441
-0.0053	-0.0053	-0.0053	-0.0003

-1.274	-1.2631	0.3977	0.7793
-0.6546	-0.6546	-0.6546	-0.7821
6.5877	4.7324	10.7352	6.8906
-1	-1	-1	-1
-63.392	-5.4202	-6.7719	-99.6748
0	0	0	0
-2.2935	-2.21	-1.235	-1.448
-0.1084	-0.1084	-0.1084	-0.0738
-7.9129	-5.9165	-7.6278	-10.5297
0	0	0	0

Notes: The t-tilde-bar $(\tilde{\mathbf{t}}-\mathbf{bar}_{\mathbf{NT}})$ statistic is similar to the t-bar$(\mathbf{t}-\mathbf{bar}_{\mathbf{NT}})$, statistic except a different error variance estimator of the Dickey-Fuller regression is used. A standardised version of the statistic t-tilde-bar is $-\mathbf{t}-\mathbf{tilde}-\mathbf{bar}(\mathbf{Z}_{\tilde{\mathbf{t}}-\mathbf{bar}})$. In presence of serial correlation, Dickey-Fuller regression is augmented as follow : $\Delta\mathbf{y}_{\mathbf{it}}=\boldsymbol{\phi}_{\mathbf{i}}\mathbf{y}_{\mathbf{i,t-1}}+\mathbf{z}_{\mathbf{it}}^{'}\boldsymbol{\gamma}_{\mathbf{i}}+\sum_{\mathbf{j=1}}^{\mathbf{p}}\Delta\mathbf{y}_{\mathbf{i,t-j}}+\boldsymbol{\epsilon}_{\mathbf{i,t}}$ where $\mathbf{p}$ is the number of lags. Im et al. (2003) propose thus another statistic noted $\mathbf{W}_{\mathbf{t-bar}}$ which follows an asymptotical standard normal distribution when $\mathbf{T}\to\infty$ followed by $\mathbf{N}\to\infty$.

Table 2: original data for developed countries

	Fisher-type tests							
Variables	Fisher-ADF statistic				Fisher-PP statistic			
	P	Z	L*	Pm	P	Z	L*	Pm
stock price	7.0642	-0.3116	-0.3876	1.0834	1.7252	1.8686	2.3419	-0.8043
(p-value)	-0.1325	-0.3777	-0.3521	-0.1393	-0.7861	-0.9692	-0.9828	-0.7894
stock return	68.7811	-7.6302	-13.9546	22.9036	116.2475	-10.1402	-23.5847	39.6855
(p-value)	0	0	0	0	0	0	0	0
IDE	65.2805	-7.3867	-13.2443	21.6659	120.8047	-10.4345	-24.5093	41.2967
(p-value)	0	0	0	0	0	0	0	0
exchange rate	15.478	-2.8791	-3.123	4.0581	2.8068	-0.0151	-0.0138	-0.4219
(p-value)	-0.0038	-0.002	-0.0037	0	-0.0907	-0.094	-0.0846	-0.0634
interest rate	12.794	-2.3703	-2.5325	3.1091	14.6597	-2.1255	-2.6912	3.7688
(p-value)	-0.0123	-0.0089	-0.012	-0.0009	-0.0055	-0.0168	-0.0088	-0.0001
M1	4.3007	-0.1505	-0.1548	0.1063	0.7947	2.1685	2.4883	-1.1332
(p-value)	-0.3668	-0.4402	-0.4396	-0.4577	-0.9392	-0.9849	-0.987	-0.8714
Ln(M1)	33.2091	-4.9197	-6.7373	10.327	90.8603	-8.4069	-18.434	30.7098
(p-value)	0	0	0	0	0	0	0	0
IPC	17.1045	-3.0697	-3.452	4.6331	3.4277	-0.2653	-0.2436	-0.2024
(p-value)	-0.0018	-0.0011	-0.0019	0	-0.489	-0.3954	-0.4055	-0.5802
Ln(IPC)	96.221	-9.2172	-19.5217	32.605	132.1098	-10.9496	-26.8029	45.2937
(p-value)	0	0	0	0	0	0	0	0

Notes: The t-tilde-bar $(\tilde{\mathbf{t}}-\mathbf{bar}_{\mathbf{NT}})$ statistic is similar to the t-bar$(\mathbf{t}-\mathbf{bar}_{\mathbf{NT}})$, statistic except a different error variance estimator of the Dickey-Fuller regression is used. A standardised version of the statistic t-tilde-bar is $-\mathbf{t}-\mathbf{tilde}-\mathbf{bar}(\mathbf{Z}_{\tilde{\mathbf{t}}-\mathbf{bar}})$. In presence of serial correlation, Dickey-Fuller regression is augmented as follow : $\Delta\mathbf{y}_{\mathbf{it}}=\boldsymbol{\phi}_{\mathbf{i}}\mathbf{y}_{\mathbf{i,t-1}}+\mathbf{z}_{\mathbf{it}}^{'}\boldsymbol{\gamma}_{\mathbf{i}}+\sum_{\mathbf{j=1}}^{\mathbf{p}}\Delta\mathbf{y}_{\mathbf{i,t-j}}+\boldsymbol{\epsilon}_{\mathbf{i,t}}$ where $\mathbf{p}$ is the number of lags. Im et al. (2003) propose thus another statistic noted $\mathbf{W}_{\mathbf{t-bar}}$ which follows an asymptotical standard normal distribution when $\mathbf{T}\to\infty$ followed by $\mathbf{N}\to\infty$.

Table 2. (continued)

IPS test			
t-bar	t-tilde-bar	Z-t-tilde-bar	W-t-bar
0.1243	0.119	2.7807	1.8973
-0.9973	-0.9973	-0.9973	-0.9711
-2.40E+02	-7.2298	-9.8926	-3.80E+02
0	0	0	0
-8.5844	-6.1902	-8.0977	-6.2035
0	0	0	0
-1.3991	-1.3907	0.1777	-0.5566
-0.0705	-0.0705	-0.0705	-0.0889
-2.7845	-2.6094	-1.9236	-1.6477
-0.0272	-0.0272	-0.0272	-0.0497
0.0795	0.0769	2.7081	2.3142
-0.9966	-0.9966	-0.9966	-0.9897
-35.5134	-6.5065	-8.6452	-56.0386
0	0	0	0
-1.6055	-1.5896	-0.1654	-0.2744
-0.4343	-0.4343	-0.4343	-0.3919
-14.1074	-7.1344	-9.7281	-17.1522
0	0	0	0

Notes: The t-tilde-bar ($\mathbf{\tilde{t} - bar_{NT}}$) statistic is similar to the t-bar($\mathbf{t - bar_{NT}}$), statistic except a different error variance estimator of the Dickey-Fuller regression is used. A standardised version of the statistic t-tilde-bar is $\mathbf{-t - tilde - bar}(\mathbf{Z_{\tilde{t}-bar}})$. In presence of serial correlation, Dickey-Fuller regression is augmented as follow: $\Delta \mathbf{y_{it}} = \boldsymbol{\phi}_\mathbf{i}\mathbf{y_{i,t-1}} + \mathbf{z'_{it}}\boldsymbol{\gamma}_\mathbf{i} + \sum_{\mathbf{j=1}}^{\mathbf{p}} \Delta \mathbf{y_{i,t-j}} + \boldsymbol{\epsilon}_\mathbf{i,t}$ where $\mathbf{p}$ is the number of lags. Im et al. (2003) propose thus another statistic noted $\mathbf{W_{t-bar}}$ which follows an asymptotical standard normal distribution when $\mathbf{T} \to \infty$ followed by $\mathbf{N} \to \infty$.

Table 3: Demeaned data for emerging countries

	Fisher-type tests							
Variables	Fisher-ADF statistic				Fisher-PP statistic			
	P	Z	L*	Pm	P	Z	L*	Pm
stock price	20.5426	-3.5625	-4.163	5.8487	10.084	-1.9835	-1.9779	2.151
(p-value)	-0.0004	-0.0002	-0.0005	0	-0.039	-0.0237	-0.034	-0.0157
stock return	81.2856	-8.3892	-16.4915	27.3246	144.1746	-11.4917	-29.2507	49.5592
(p-value)	0	0	0	0	0	0	0	0
IDE	104.7765	-9.6609	-21.2574	35.6299	119.9204	-10.4016	-24.3299	40.984
(p-value)	0	0	0	0	0	0	0	0
exchange rate	19.7806	-3.4666	-4.0074	5.5793	12.784	-2.4608	-2.5598	3.1056
(p-value)	-0.0006	-0.0003	-0.0006	0	-0.0124	-0.0069	-0.0113	-0.0009
interest rate	14.2696	-2.6976	-2.8718	3.6309	3.6412	-0.3495	-0.3209	-0.1268
(p-value)	-0.0065	-0.0035	-0.0062	-0.0001	-0.4567	-0.3634	-0.3765	-0.5505
M1	0.4623	1.7411	1.7039	-1.2508	0.5968	0.2547	0.9852	-1.4142
(p-value)	-0.9771	-0.9592	-0.9448	-0.8945	-1	-1	-1	-0.9214
Ln(M1)	18.1863	-3.2587	-3.6811	5.0156	8.6286	-1.6928	-1.6508	1.6365
(p-value)	-0.0011	-0.0006	-0.0012	0	-0.0711	-0.0452	-0.0452	-0.0509
IPC	10.8548	-2.127	-2.1466	2.4235	3.8797	-0.4353	-0.4004	-0.0425
(p-value)	-0.0282	-0.0167	-0.0249	-0.0077	-0.4225	-0.3317	-0.3475	-0.517
Ln(IPC)	66.3639	-7.4761	-13.4642	22.049	87.1656	-8.724	-17.6845	29.4035

(p-value)	0	0	0	0	0	0	0	0

Notes: The t-tilde-bar ($\mathbf{\tilde{t} - bar_{NT}}$) statistic is similar to the t-bar($\mathbf{t - bar_{NT}}$), statistic except a different error variance estimator of the Dickey-Fuller regression is used. A standardised version of the statistic t-tilde-bar is $\mathbf{-t - tilde - bar(Z_{\tilde{t}-bar})}$. In presence of serial correlation, Dickey-Fuller regression is augmented as follow : $\Delta \mathbf{y_{it}} = \mathbf{\phi_i y_{i,t-1}} + \mathbf{z'_{it}\gamma_i} + \sum_{j=1}^{p} \Delta \mathbf{y_{i,t-j}} + \mathbf{\epsilon_{i,t}}$ where $\mathbf{p}$ is the number of lags. Im et al. (2003) propose thus another statistic noted $\mathbf{W_{t-bar}}$ which follows an asymptotical standard normal distribution when $\mathbf{T} \rightarrow \infty$ followed by $\mathbf{N} \rightarrow \infty$.

Table 3: continued

IPS test			
t-bar	t-tilde-bar	Z-t-tilde-bar	W-t-bar
-2.682	-2.5827	-1.8776	-1.9045
-0.0302	-0.0302	-0.0302	-0.0284
-9.7395	-6.5728	-8.7597	-13.5414
0	0	0	0
-8.5435	-6.1798	-8.0797	-10.6728
0	0	0	0
-3.13	-2.9691	-2.5438	-1.4634
-0.0055	-0.0055	-0.0055	-0.0717
-1.7208	-1.6998	-0.3553	-0.3196
-0.3612	-0.3612	-0.3612	-0.3746
4.5169	4.0472	9.5538	4.5172
-1	-1	-1	-1
-2.4058	-2.3357	-1.4524	-2.8342
-0.0732	-0.0732	-0.0732	-0.0023
-1.7764	-1.7527	-0.4465	0.0075
-0.3276	-0.3276	-0.3276	-0.503
-7.1245	-5.5735	-7.0362	-9.2297
0	0	0	0

Notes: The t-tilde-bar ($\mathbf{\tilde{t} - bar_{NT}}$) statistic is similar to the t-bar ($\mathbf{t - bar_{NT}}$), statistic except a different error variance estimator of the Dickey-Fuller regression is used. A standardised version of the statistic t-tilde-bar is $\mathbf{-t - tilde - bar(Z_{\tilde{t}-bar})}$. In presence of serial correlation, Dickey-Fuller regression is augmented as follow : $\Delta \mathbf{y_{it}} = \mathbf{\phi_i y_{i,t-1}} + \mathbf{z'_{it}\gamma_i} + \sum_{j=1}^{p} \Delta \mathbf{y_{i,t-j}} + \mathbf{\epsilon_{i,t}}$ where $\mathbf{p}$ is the number of lags. Im et al. (2003) propose thus another statistic noted $\mathbf{W_{t-bar}}$ which follows an asymptotical standard normal distribution when $\mathbf{T} \rightarrow \infty$ followed by $\mathbf{N} \rightarrow \infty$.

Table 4: Demeaned data for developed countries.

Variables	Fisher-type tests							
	Fisher-ADF statistic				Fisher-PP statistic			
	P	Z	L*	Pm	P	Z	L*	Pm
stock price	13.9559	-2.6489	-2.8063	3.5199	3.6091	-0.3376	-0.3376	-0.1382
(p-value)	-0.0074	-0.004	-0.007	-0.0002	-0.4615	-0.3678	-0.3806	-0.555
stock return	71.434	-7.7979	-14.4928	23.8415	88.5199	-8.7996	-17.9592	29.8823
(p-value)	0	0	0	0	0	0	0	0
IDE	58.6827	-6.9628	-11.9058	19.3333	116.2315	-10.2259	-23.5815	39.6798
(p-value)	0	0	0	0	0	0	0	0
exchange rate	15.3753	-2.8644	-3.1018	4.0218	2.9659	-0.0837	-0.0766	-0.3656
(p-value)	-0.004	-0.0021	-0.0039	0	-0.5635	-0.4667	-0.47	-0.6427
interest rate	7.1638	-1.3674	-1.3053	1.1186	0.5196	1.6489	1.6031	-1.2305
(p-value)	-0.1275	-0.0858	-0.1064	-0.1317	-0.9716	-0.9504	-0.9344	-0.8907
M1	11.0669	-2.1654	-2.1926	2.4985	1.5815	0.6356	0.5873	-0.8551
(p-value)	-0.0258	-0.0152	-0.0229	-0.0062	-0.8121	-0.7375	-0.7168	-0.8037
Ln(M1)	31.8359	-4.7941	-6.4587	9.8415	29.714	-4.5844	-6.028	9.0913
(p-value)	0	0	0	0	0	0	0	0
IPC	18.7034	-3.3273	-3.787	5.1985	2.9136	-0.0614	-0.0562	-0.3841
(p-value)	-0.0009	-0.0004	-0.001	0	-0.5724	-0.4755	-0.478	-0.6496
Ln(IPC)	93.8584	-9.0901	-19.0423	31.7697	107.3269	-9.788	-21.7749	36.5316
(p-value)	0	0	0	0	0	0	0	0

Notes: The t-tilde-bar ($\tilde{\mathbf{t}} - \mathbf{bar_{NT}}$) statistic is similar to the t-bar($\mathbf{t} - \mathbf{bar_{NT}}$), statistic except a different error variance estimator of the Dickey-Fuller regression is used. A standardised version of the statistic t-tilde-bar is $-\mathbf{t} - \mathbf{tilde} - \mathbf{bar}(\mathbf{Z_{\tilde{t}-bar}})$. In presence of serial correlation, Dickey-Fuller regression is augmented as follow : $\Delta \mathbf{y_{it}} = \boldsymbol{\phi}_{\mathbf{i}}\mathbf{y_{i,t-1}} + \mathbf{z}'_{\mathbf{it}}\boldsymbol{\gamma}_{\mathbf{i}} + \sum_{\mathbf{j=1}}^{\mathbf{p}} \Delta \mathbf{y_{i,t-j}} + \boldsymbol{\epsilon}_{\mathbf{i,t}}$ where $\mathbf{p}$ is the number of lags. Im et al. (2003) propose thus another statistic noted $\mathbf{W_{t-bar}}$ which follows an asymptotical standard normal distribution when $\mathbf{T} \to \infty$ followed by $\mathbf{N} \to \infty$.

Table 4: (continued)

IPS test			
t-bar	t-tilde-bar	Z-t-tilde-bar	W-t-bar
-1.5562	-1.5424	-0.0839	-1.5746
-0.4666	-0.4666	-0.4666	-0.0577
-7.1616	-5.5912	-7.0667	-6.7188
0	0	0	0
-8.391	-6.1221	-7.9802	-0.3571
0	0	0	-0.3605
-1.3959	-1.3876	0.1831	-0.2411
-0.5726	-0.5726	-0.5726	-0.4047
-0.5485	-0.5509	1.6256	1.6134
-0.948	-0.948	-0.948	-0.9467
-1.0134	-1.0132	0.8286	-0.0379
-0.7963	-0.7963	-0.7963	-0.4849
-4.2727	-3.8686	-4.096	-4.5275
0	0	0	0
-1.5236	-1.511	-0.0297	0.1737
-0.4881	-0.4881	-0.4881	-0.569
-7.9854	-5.9518	-7.6886	-4.9146
0	0	0	0

Notes: The t-tilde-bar ($\tilde{\mathbf{t}} - \mathbf{bar_{NT}}$) statistic is similar to the t-bar($\mathbf{t-bar_{NT}}$), statistic except a different error variance estimator of the Dickey-Fuller regression is used. A standardised version of the statistic t-tilde-bar is $\mathbf{-t-tilde-bar}(\mathbf{Z}_{\tilde{t}-bar})$. In presence of serial correlation, Dickey-Fuller regression is augmented as follow : $\mathbf{\Delta y_{it} = \phi_i y_{i,t-1} + z_{it}^{'}\gamma_i + \sum_{j=1}^{p} \Delta y_{i,t-j} + \epsilon_{i,t}}$ where $\mathbf{p}$ is the number of lags. Im et al. (2003) propose thus another statistic noted $\mathbf{W_{t-bar}}$ which follows an asymptotical standard normal distribution when $\mathbf{T} \rightarrow \infty$ followed by $\mathbf{N} \rightarrow \infty$.

4 Empirical results

We follow the Panel VAR approach which combines the classical VAR approach and the Panel data approach. The model to be estimated is the following:

$$\mathrm{SP}_{i,t} = \alpha_0 + \alpha_1 \mathrm{LnSP}_{i,t-1} + \alpha_2 \mathrm{FDI}_{i,t-1} + \alpha_3 \mathrm{ER}_{i,t-1} + \alpha_4 \mathrm{Ln(CPI)}_{i,t-1} + \alpha_5 \mathrm{LnM1}_{i,t-1} + \alpha_6 (\mathrm{IR})_{i,t-1} + \varepsilon_{i,t} \qquad (13)$$

With $i = 1, \dots, n = 81\ ;\ t = 1995T1, \dots, 2015T1.$

The description and measurement of variables is explained in table 5 as shown.

Table 5: Definition and measurements of variables

Type	Variable	Variable Transformation and Measure
Dependent variable	Stock return	$R_t = LnP_t - Ln\,P_{t-1}$
Independent variables	Foreign Direct investment	FDI
	Nominal exchange rate	ER
	Inflation	Ln (CPI)
	Money supply	Ln(M1)
	Interest rate	IR

We transformed some variable in (Ln) if series are I (1) or not stationary.

The Panel VAR model estimations are done with STATA 12 software because of its performance in Panel data based studies. Empirical model estimation results are represented by the equation (13) and reported in the tables below.

This analysis objective is consists in determine the optimum number of lags (p) of the on level model. For the dependent variable, the optimal lag choice needs an identification model. Brooks (2002) suggests the existence of two ways to select the optimal lag. The first way, is based on the data frequency (daily data, intraday …) here the optimal lag choice is not evident. The second way applies the information criteria. In fact, there exist three criteria such as the AIC (1974), the SBIC and the HQIC (1978) criteria. In our empirical approach, we often adopt the SBIC criteria to identify the optimal lag length because it requires a more severe penalty AIC criterion. By referring to the SBIC criteria, obtained optimal lag is in the order of one for the two groups of emerging and developed countries. Tables (6) and (7) allow the choice of the optimal lag.

Svestre (2002) indicates that standard econometric techniques such as OLS do not provide efficient parameters estimations in a dynamic model which proposes the lagged dependent variable as explicative variable. Furthermore, the estimation of model with random effects using OLS is not efficient because there is a correlation between individual effects and estimators (Biondi and Toneto, 2008). For this, we propose to estimate with GMM method in system because this method provides solutions to different problems such as simultaneity bias and reverse causality bias.

GMM estimator on system is proposed by Arellano and Bover (1995) and Blundel and Bond (1998). This empirical method assumes that equations in difference are used as variables in level tools. Monte Carlo simulations realized Blundel and Bond (1998) proved that the GMM estimator in system is more efficient than the one in first difference. Table 8 and 9 report the estimate results for the VAR model from the six variables.

Table 6: Optimal lag (emerging countries)

Emerging countries								
Lag	**LL**	**LR**	**DL**	**P**	**FPE**	**AIC**	**HQIC**	**SBIC**
0	-13529.8				2.90E+32	91.768	91.798	91.843
1	-11869.6	3320.4	36	0	4.80E+27	80.7564	80.9666*	81.2814*
2	-11836.8	65.503	36	0.002	4.90E+27	80.7785	81.1688	81.7533
3	-11809.7	54.339	36	0.026	5.20E+27	80.8383	81.4088	82.2631
4	-11771.5	76.355	36	0	5.10E+27	80.8236	81.5742	82.6983
5	-11639.3	264.4*	36	0	2.7e+27*	80.1714*	81.1022	82.496

Table 7: Optimal lag (developed countries)

Pays développés

Lag	LL	LR	DL	P	FPE	AIC	HQIC	SBIC
0	-5940.38				1.30E+22	67.9586	68.0026	68.0671
1	-4921.23	2038.3	36	0	1.70E+17	56.7226	57.0307	57.4821*
2	-4837.94	166.58	36	0	1.00E+17	56.1821	56.7543*	57.5927
3	-4801.73	72.404	36	0	1.00E+17	56.1798	57.0161	58.2415
4	-4759.21	85.057	36	0	9.50E+16	56.1052	57.2055	58.8179
5	-4689.29	139.83*	36	0	6.5e+16*	55.7176*	57.082	59.0813

In emerging countries, empirical results indicate that the response of stock returns to the foreign direct investment shock is negative and significant. The response of stock returns to an exchange rate shock is positive and no significant. This finding is consistent with the argument that exchange rate appreciation leads to an increase in stock returns, at least from the international investor's perspective (e.g., Bilson et al., 2001; Pebbles & Wilson, 1996). The response of stock returns to the interest rate is negative and significant, implying that the more nominal interest rates lead to a decrease in market returns. The response of stock returns to the money supply is negative and no significant. This finding is not surprising since an increase in money supply can lead to higher inflation and lower returns. Finally the response of stock returns to consumer price index is negative and no significant. Economically, any decrease in expected level of economic activity should induce a less level of return (Cheung et al., 1997a).

Table 8: Empirical results from VAR modeling (emerging countries)

Emerging countries

response of	response to					
	stock return (t-1)	FDI (t-1)	ER(t-1)	IR (t-1)	Ln M1 (t-1)	Ln IPC (t-1)
stock return (t)	-0.014	0.0087	2.56E-07	3.85E-06	-6.20E-06	0.0001
	[-0.1556]	[0.9609]	[0.3320]	[0.7706]	[-0.5228]	[1.7077]
FDI (t)	-0.7895*	0.0170	1.11E-06	2.01E-07	-0.0002	0.0008*
	[-1.9810]	[0.1492]	[0.5371]	[0.0063]	[-1.7280]	[2.1404]

ER (t)	4163.339	755.1975	0.8195*	0.1821	5.0308*	8.1364*
	[0.5080]	[0.9935]	[11.1305]	[0.3781]	[3.9460]	[2.2816]
IR (t)	-2.46E+02*	-3.30E+01	0.0017	0.9518*	-0.4161*	-0.1319
	[-1.9774]	[-0.9071]	[1.2243]	[35.6128]	[-7.6500]	[-0.4934]
Ln M1 (t)	-23.3147	1.9447	-0.0004*	-0.0025	0.0094*	0.0248
	[-0.9581]	[0.7669]	[-2.1359]	[-1.6489]	[2.0504]	[1.5692]
Ln IPC (t)	-18.677	-28.3053	0.0004	0.0150*	0.0067	0.0878
	[-0.3204]	[-1.6117]	[0.6756]	[2.3775]	[0.3072]	[1.0537]

N= 162 observations

Note: the value between brackets indicates the standard deviation

In developed countries, the response of stock returns to macroeconomic variables is constant and stable. This finding indicates that financial markets in these countries are integrated and information is not asymmetric. Economically, stability is reached when short run equilibrium values converge to the long run one. For emerging countries, we observe an alternating in the variables movements. The Instability is reached when short run equilibrium values do not converge to the long run one.

Table 9: Empirical results from VAR modeling (Developed countries)

	Developed countries					
response of	response to					
	stock return (t-1)	FDI (t-1)	ER(t-1)	IR (t-1)	Ln M1 (t-1)	Ln IPC (t-1)
stock return (t)	0.2711	0.5593	-1.16E-07	0.0003*	-0.0001	-0.0006
	[1.8590]	[0.8634]	[-0.7452]	[2.0425]	[-1.2285]	[-1.3549]
FDI (t)	-0.0714	-1.2008	-2.70E-09	-4.59E-06	-0.00003	-0.0002
	[-0.6738]	[-1.2454]	[-0.0125]	[-0.3327]	[-0.4679]	[-0.5909]
ER (t)	23454.067	441337.1	1.0360*	4.7648	53.7089	150.3681
	[0.5529]	[1.4626]	[4.8723]	[0.4341]	[-1.4013]	[1.0028]
IR (t)	49.2895	1409.843	-0.00008	0.9799*	0.2924*	0.6591
	[0.3094]	[1.0384]	[-0.0645]	[16.093]	[-1.9884]	[1.0377]
Ln M1 (t)	-40.2704	13.6024	-0.00007	-0.0022	-0.0024	0.1843*
	[-1.3720]	[0.0922]	[-0.9029]	[-0.4055]	[-0.0786]	[1.9800]

Ln IPC (t)	55.2145	252.248	0.00007	0.0055	-0.0504	0.0986
	[1.2037]	[0.8278]	[0.9649]	[0.7599]	[-1.2257]	[0.5287]

N= 162 observations

Note: the value between brackets indicates the standard deviation

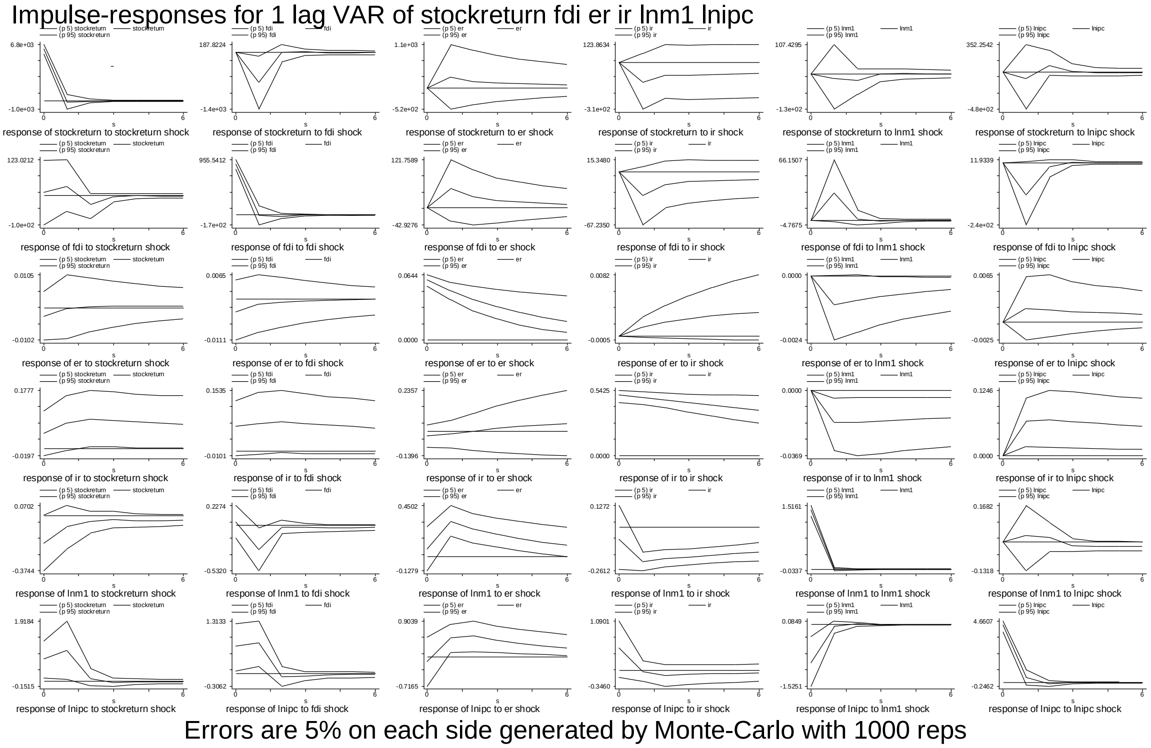

Fig1: IRF (Emerging countries)

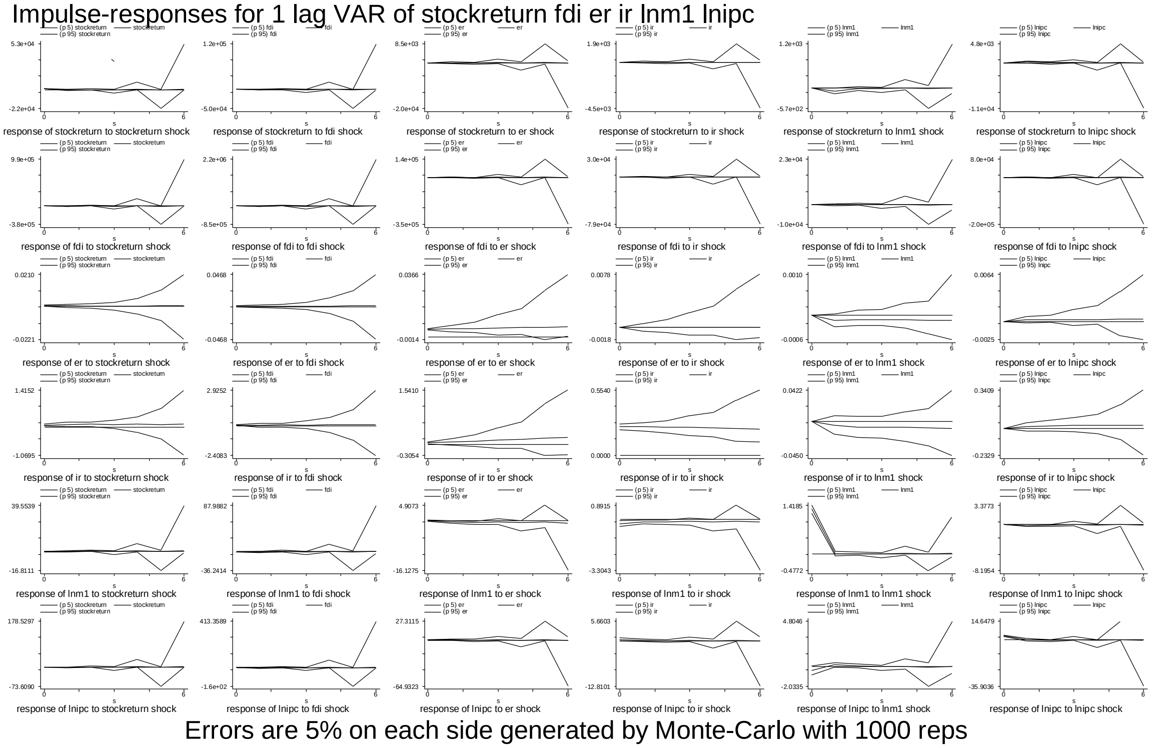

Fig 2: IRF (Developed countries)

5 Conclusion and Policy implications

Exchange rates and stock prices volatility occupy a growing presence on financial markets. Macroeconomic variables such as interest rate, inflation indicators, the money supply and exchange rate have a considerable effect on prices fluctuations. In this framework, we tried to model the existing relations between macroeconomic variables and the stock exchange volatility by the use of Panel VAR model. Estimation results and according to IRF, there is variables movements alternation explained by shocks destabilization relative to emerging countries. For developed countries, results show that the shock effect is stabilizer.

Economically, macroeconomic variables effect on stock market volatility depends mainly on investors anticipations explained by the arbitrage and also by the shock persistence effects. In facts, when investors anticipate the interest rate increase, the arbitrage is favorable to buy domestic securities. Interest rate rise induces an increase of the securities yields denominated in national currency. In the exchange market, there will be an excess of national currency demand and its appreciation. The currency appreciation increases the foreign investors’ profit denominated in local currency, which constitutes the foreign direct investment attractiveness.

Furthermore, when investors anticipate that the shock is going to persist over the time, they are going to sell their stock of capital account and leave the financial market. On the exchange market, there will be an excess of foreign currency demand and an appreciation of the latter. The national currency depreciation increases exports flows, increases the exporting firms profit and appreciates their stock exchange values.

The approaches of determination of exchange rate such as the portfolio equilibrium approach allow clarifying this theoretical link between the stock exchange volatility and macroeconomic variables. According to the exchange rate monetary approach, the determination of the exchange rate is made by the use of confrontation between the supply and the demand of real cash. Any imbalance in the currency market has an effect on the exchange rate.

Finally, we can say that the continuation and the persistency of the shock on long horizon make favorable the investment in business sectors more oriented to domestic markets because the more stock market price is volatile, the more is risky. Investor tries to minimize foreign exchange risk. Indeed, the more company is indebted and risky, the more the price is supposed to be volatile: it is the “indebtedness effect”. The investor is going to ask for a surplus premium risk to hedge its foreign exchange rate exposure and remunerate actives which became more and more risky. So, the high uncertainty is considered harmful since it brakes investment decisions and generates hedging costs.

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